Ozone alerts and asthma exacerbations: a case study of Dallas-Fort Worth 2000-2008

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Health Services Organization and Policy and Economics)
in The University of Michigan
2010

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Dedication

To my husband, Philip Carls

Acknowledgements

Thank you to Thomson Reuters for allowing me to use part of the MarketScan database for my research. I am also grateful for use of the ozone alert data, provided by Ms. Debbie Maldonado at the Texas Commission on Environmental Quality.

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List of Abbreviations

AHRQ	Agency for Healthcare Research and Quality
AQS	Air Quality System
CBA	Cost Benefit Analysis
CCAE	Commercial Claims and Encounters
CFR	Congressional Federal Record
CO	Carbon monoxide (gas)
COPD	Chronic obstructive pulmonary disease
EPA	Environmental Protection Agency (US)
EPO	Exclusive Provider Organization, health plan with an incentive to use network providers, a PCP is assigned, patients must have a referral from the PCP to see a specialist, out of network services are not covered, the plan is not financed with capitation.[a]
ER	Emergency Room
HEDIS	Healthcare Effectiveness Data and Information Set
HIPAA	Health Insurance Portability and Accountability Act
HMO	Health Maintenance Organization, a health plan where patients are assigned a PCP, must obtain a referral from the PCP to see a specialist, out of network care is not covered, and the plan is financed with a capitated payment.[a]
ICD-9-CM	International Classification of Diseases, 9th revision, clinical modification
IQR	Interquartile range, the 25th and 75th percentile
LABA	Long-acting beta$_2$-agonist, a group of long-term controller asthma medications taken daily with an inhaler
MSA	Metropolitan statistical area, population > 350,000
NAAQS	National Ambient Air Quality Standards (ambient = ground

	level)
NAEPP	National Asthma Education and Prevention Program
NCDC	National Climatic Data Center
NDC	National Drug Codes
NO_2	nitrogen dioxide (gas)
NO_x	nitrogen oxides, such as NO_2 and other combinations of nitrogen and oxygen (gas)
NOAA	National Oceanic and Atmospheric Administration
O_3	Ground-level ozone (gas)
OSC	oral systemic corticosteroids, a medication that may be provided as a pill (or intravenously at the hospital) typically for a 5-10 course after a serious asthma exacerbation
PCP	Primary Care Physician
PM	particulate matter (suspended solid matter in the air, any size)
$PM_{2.5}$	fine particulates, small particulates that contribute to summer smog or haze, defined as particulates with size <2.5 µm (micrometers)
PM_{10}	Particulates with size <10 µm (micrometers)
PPO	Preferred Provider Organization, plan that includes patient incentive to use certain providers but no primary care physician (PCP) is assigned/required, referrals from the PCP are not required to see a specialist, out of network care is covered, financing is not capitated.[a]
SABA	Short-Acting $Beta_2$-Agonist, the most common rescue inhaler used by asthma patients to self-treat asthma exacerbations
SO_2	sulfur dioxide (gas)
SO_x	sulfur oxides, such as SO_2 and other multiples of oxygen with sulfur
TCEQ	Texas Commission on Environmental Quality

[a.] Health plan definitions are based on the definitions used to classify plans in MarketScan and may not apply to other data sources.

Chapter 1 Introduction

Air quality continues to be an important health issue in many parts of the U.S., despite large improvements experienced in the past 30 years. Congress passed a series of Clean Air Acts in the 1960s which culminated in the 1970 Clean Air Act. This bill has served as the basis of air pollution control policy in the U.S. and has been amended over the years, notably in 1977, 1990 and 2005. One of the goals of the 2005 amendment was to reduce respiratory and cardiovascular disease by drastically reducing fine particulates. Recent evidence on the contribution of fine particulates to cardiovascular morbidity and mortality motivated the U.S. EPA to tighten fine particulate standards in 2006. In February 2009, a federal appeals court ordered the EPA to reconsider and possibly tighten their standards for particulate matter, ruling that Bush administration standards were "contrary to law and unsupported by adequately reasoned decision making" (Dean 2009).

One of the public responses to poor air quality has been the development of air quality warning systems. All Metropolitan Statistical Areas (MSAs) with a population greater than 350,000 are required to report air quality levels at least 5 days a week (Part 58.4 of 40 CFR). The air quality report must include the reporting area and duration, air quality level, and the responsible pollutant (U.S EPA 2006). In addition to disseminating information about current air quality, often in real-time, many cities participate in air quality forecasting programs. These forecasts were recently standardized by the AirNow program in 2002 and are intended to help the public avoid harmful exposures (EPA 1999; EPA 2003; EPA 2006b). Local agencies may also advise citizens and business to take measures to avoid activities that contribute to pollution (TCEQ 2008), although this is not part of the nationally standardized advisories. Local agencies forecast expected air quality for the next day or days and this information is then disseminated

to a range of media outlets with specific advice depending on the alert levels. The most common forecast (orange alert) advises that the air may be unhealthy for sensitive people (children, elderly, people with respiratory or cardiovascular conditions) and these people should avoid outdoor activity (EPA 2006b). About 300 cities currently participate in forecasting programs and report their forecasts to the EPA's AirNow program.

A few studies have examined the role of air quality forecasts in protecting health and suggest that ignoring ozone alerts results in a biased the observed relationship between air quality and health. Neidell used hospital discharge data from Southern California and found evidence that ozone alerts are protective and ignoring ozone alerts biases the health effect of ozone for children and the elderly, but not adults. He also examined data on visits to outdoor attractions and found that people avoided outdoor activity on ozone alert days (Neidell 2009a; Neidell 2009b). Using the same data, researchers also found evidence that the cost of intertemporal substitution of activities increased over the duration of a poor air quality episode. Air pollution avoidance responses, in terms of changes in activities, were larger on the first day of the episode but largely disappeared by the second day (Graff Zivin and Neidell 2009). In another study, Moretti and Neidell did not study alerts per se, but tried to measure the unbiased health effects of ozone using an exogenous source of variation in ozone levels: boat traffic at the port of Los Angeles. The authors argue that variation caused by boat traffic is exogenous because it is not incorporated into ozone forecasts and the public is largely unaware of when boats come to port. They find that health effects identified based on boat traffic (using instrumental variables) are much higher than standard methods, supporting the hypothesis that observational studies that ignore ozone alerts may have a downward bias (Moretti and Neidell 2008).

Understanding avoidance behavior is important for a variety of reasons. First, it suggests that public information about air quality can be used as a policy lever to protect health, beyond simply setting standards. Second, if avoidance behavior is important, the epidemiological studies that have been used to set air quality standards

may underestimate the biological effect of air pollutants and may yield misleading results when used in a Cost Benefit Analysis (CBA). For example, if people respond to forecasts by staying indoors, their personal exposure will then be less than what is measured at a community monitor (ambient exposure). Random measurement error increases variance, but does not bias estimates. However, this source of measurement error is non-random; it is larger on days with high ozone levels since those days are more likely to have an ozone alert. Ignoring air pollution alerts will bias observed effects of pollution to zero when exposure is measured using community monitors, the most common method of measuring exposure in non-experimental studies. One of the implications of ignoring this bias is that air quality standards may not provide adequate protection for vulnerable groups, such as outdoor workers who cannot avoid exposure.

The reduced form relationship that ignores avoidance behavior may be appropriate for setting standards locally. For example, suppose relationships observed in Dallas are used to set standards for Dallas. However, standards are set nationally and the reduced form relationships are likely to be different across the country, due in part to different costs of avoiding exposure to poor air quality and differences in alert programs. For example, it may be relatively less costly to avoid exposure to air pollutants in cities where central air conditioning is widespread than in areas with more limited air conditioning. In cities without air conditioning, windows may be left open during the warm months, promoting airflow from the outside which increases exposure to outdoor air pollutants. Thus it is difficult to avoid exposure to air pollutants on hot days without air conditioning, but easier to avoid exposure on hot days in locations where central air is common.

Study Objectives

The first two objectives of this study are to assess (1) if information about air quality forecasts is protective of health and (2) if it alters the observed relationship between asthma exacerbations and air quality. People with asthma are specifically mentioned in the ozone advisories as a sensitive group and thus may be more likely to

respond to ozone forecasts than the general population. A wide range of evidence from animal models, controlled human clinical studies, and epidemiological studies indicate that people with asthma are particularly susceptible to respiratory problems when exposed to levels of ozone commonly experienced in the U.S. (EPA 2006a).

The third objective is to test a new measure of asthma exacerbations, fills of oral systemic corticosteroids (OSC). For people with asthma, oral systemic corticosteroids are provided almost exclusively as a short-term course to treat an acute exacerbation. Guidelines do not recommend that patient have OSCs on-hand, unless the person has experienced life-threatening asthma attacks (NAEPP 2002). The rationale is that there are other medications better suited for quick-relief with fewer side effects. Symptom relief from oral systemic corticosteroids typically takes hours while symptom relief from rescue medications often occurs within minutes. Thus OSC fills are closely related in time to the event that triggered the asthma attack. This is important because in medical claims data, I observe when a prescription is filled, but not when the drug was actually used.

I am not aware of any other studies that use OSC fills of systemic corticosteroids to measure asthma exacerbations. Most studies with a medication based measure have examined use of rescue medications or long-term controllers. This is possible because these other studies have information on actual use (e.g. from daily diaries or school nurse records), so they are able to link use of the medication with asthma triggers. One previous study linked fills of rescue medications by Medicaid recipients to air quality and found that worse air quality was associated with increases in fills of rescue medications, using a similar identification strategy employed in this study (Gu and Rathouz 2004).

This new measure of asthma exacerbations has the potential to significantly contribute to our understanding of asthma and air pollution because it can be measured in claims data, which typically provide larger samples than can be obtained from diary or direct observation data. Furthermore, this measures a lower level of morbidity that may affect a larger share of asthma patients and thus have a higher cost burden than hospitalizations or emergency room visits.

The fourth objective is to assess whether fine particulates confound the relationship between ozone and health effects. Clinical evidence suggests that both ozone and fine particulates may increase respiratory morbidity. Air quality standards in the US are set for each pollutant separately, even though some pollutants may exacerbate health effects in the presence of other pollutants. Fine particulates have not been as extensively studied as ozone in observational studies because widespread monitoring began only in the last 10 years.

The fifth objective is to test whether children with asthma are more susceptible to air pollution than adults with asthma, as suggested by clinical and experimental evidence.

Summary of Study Approach

The approach of this study is to estimate daily time-series models of the number of people with each outcome, as a function of ozone, ozone alerts, and control variables using data from Dallas-Fort Worth 2000-2008. The main outcomes are emergency room visits for asthma, inpatient stays for asthma, doctor office visits for asthma, fills of oral systemic corticosteroids (OSC) and fills of rescue inhalers. All patients in the study lived in the Dallas-Fort Worth Metroplex and were enrolled in health plans offered by over 75 large, mostly self-insured, employers. The Dallas-Fort Worth Metroplex has the distinction of being ranked by the American Lung Association as the 7th worst city for ozone pollution (2008) but did not make the Worst 25 list for fine particulate pollution. Since all enrollees are relatively well-insured, this created a more homogenous sample (in terms of income, insurance status) but less representative than one would find in a general sample of residents of Dallas-Fort Worth.

The main analysis is based on a general sample of health plan enrollees, thus the population at risk for an asthma attack is anyone enrolled in a plan. I also examine a subset of enrollees, the asthma 2005 cohort, who were treated for asthma in 2005. Here the at-risk sample is people with asthma, where asthma is defined based on treatment in 2005. The purpose of this sensitivity analysis is to assess the differences

between studies that define their population at risk for asthma attacks as those being treated for asthma and those that allow anyone to be at risk. To a certain extent, the prevalence of asthma could be endogenous to air pollution. In years with worse air quality, more people will be treated for asthma. Some of this could be due to new cases of asthma, people who had not been treated before. Some of this increase could also be due to people who are only intermittently treated for asthma every few years. This potential endogeneity could be exacerbated in medical claims data, where the prevalence of asthma must be defined based on treatment for asthma. People with asthma who are not treated (i.e. do not generate a claim with an asthma diagnosis code or asthma medication) cannot be found in claims data. Most large scale epidemiological studies of ER visits or inpatient stays use a general sample as the at-risk population while smaller scale studies of asthma symptoms and rescue inhaler use employ an asthma cohort as the at-risk population.

In this study, I do not directly observe avoidance behavior; rather I observe the presence of ozone alerts and utilization of care for asthma. Ozone alerts are made by 2 pm the previous day and are distributed as part of the National Weather Service's weather wire, as well as to local media outlets. The alerts are also available on the internet and residents can sign up for free email alerts. Exposure to ozone can be avoided by staying indoors since ozone is highly reactive and decomposes into water and oxygen upon contact with hard surfaces. Thus ozone levels are typically very low indoors. Exposure to fine particulates can also be avoided by staying indoors as indoor levels tend to be lower if there is limited circulation with outside air, which is particularly true for buildings with central air conditioning systems. Avoiding strenuous activity can also limit harmful effects of air pollutants. Strenuous activity is related to deeper and more rapid breathing, increasing the intake of air pollutants.

This study find evidence of the protective effect of alerts and ignoring ozone alerts can bias estimates of the association between ozone and asthma inpatient stays and ER visits by 40%-200%. Mixed results were observed for OSC fills, which was sensitive to controls for seasonality. Fine particulates did not appear to confound

results; associations with ozone and ozone alerts were not sensitive to the inclusion of fine particulates in the model. Results from the general sample and asthma 2005 cohort were qualitative similar. The biggest differences in results were driven by differences in the sample in terms of the characteristics of the patients (beyond asthma) and years of data included.

I proceed as follows. Chapter 2, Background, provides information on asthma, air pollutants, exposure, health effects, and treatment of asthma. Chapter 3 discusses the data and methods and describes specific hypotheses that are tested. Chapter 4 presents results, beginning with a description of the data and concluding with the multivariate regressions. Chapter 5 discusses interpretation of results and study contributions. Tables and figures are presented at the end of the chapter in which they are first referenced. Thus most tables and figures are at the end of Chapter 4 (results). Tables of results begin on page 59 and results figures begin on page 81. An Appendix presents coefficients and standard error for most models discussed in the main analysis and begins on page 115.

Chapter 2 Background

This section motivates the approach on this study by reviewing what causes asthma exacerbations, previous evidence on the link between air pollutants and asthma exacerbations, and the ability of people to avoid exposure to air pollutants.

Asthma

Asthma is a chronic lung disease that inflames and narrows the airways. About 20 million people have asthma in the U.S. Prevalence of asthma is higher in children (8.5%) than adults (6.7%) (Moorman et al. 2007). The focus of this study is on short-term effects of air pollution on asthma exacerbations. In this subsection, I discuss causes of asthma exacerbations and treatment. Next I discuss the development of asthma.

Causes of asthma exacerbations

Asthma exacerbations are characterized by recurring symptoms of wheezing, breathlessness, chest tightness, and coughing (NAEPP 2007). Approximately 11.6 million persons reported at least one asthma attack during the preceding 12 months (Moorman et al. 2007). Of people with asthma, 55.6% had at least 1 asthma attack in the previous 12 months (Moorman et al. 2007). Children with asthma were more likely to have had an asthma attack in the previous 12 months (63.1%) compared with adults (52.2%). Asthma exacerbations may be triggered by a variety of environmental factors including: allergens, viral infections, tobacco smoke, indoor pollutants (cleaning sprays), outdoor air pollution, and stress.

Particulate matter and/or ozone have been shown to precipitate symptoms of asthma (Delfino et al. 2002; Dockery et al. 1989; Hiltermann et al. 1998; Ostro et al. 1995; Peters et al. 1999; Pope et al. 1991) and lead to increased use or fills of rescue

medications (Gent et al. 2003; Gu and Rathouz 2004; Slaughter et al. 2003). A few studies have found no association. Schildcrout et al. found an association between lags of CO and NO_2 and daily symptoms and use of rescue inhalers, but reported that PM_{10} and ozone were not associated with asthma exacerbations (Schildcrout et al. 2006). Roemer et al. reported no association between symptoms or medication use and pollutants, although ozone was not studied (Roemer et al. 1998).

Exactly how air pollution is related to asthma exacerbations is complicated by differences between individuals and the complex interaction of genetic and environmental factors. It is likely that air pollution has a direct effect by increasing inflammation that leads to airway constriction. In addition, air pollution decreases the person's lung function and makes the person susceptible to asthma attacks triggered by other factors or makes the attack worse (American Thoracic Society 2000; Trasande and Thurston 2005). There are a multitude of studies showing changes in lung structure, lung chemistry and other measureable responses to air pollution (Pope 2000; Trasande and Thurston 2005). Biological and epidemiological evidence suggests that adverse effect of air pollution can be quite quick, such as within hours or days (Pope 2000). Thus I expect patients experiencing acute health effects to interact with the health care system within a day or two of their exposure to elevated air pollution. Previous work on short-term effects typically examine daily to 1 week time scales for observing health effects, although a few use longer time scales due to data limitations (Bell et al. 2004). The documents supporting EPA standards for fine particulates and ozone emphasize same day and previous day effects over longer lags(EPA 2006a; EPA 2008).

A few studies have examined seasonal airborne allergens to determine if these may confound air pollution epidemiological studies. All of these studies have found that effects of pollutants were robust to inclusion of controls for seasonal allergens (i.e. pollen, mold, spores) in studies of the short-term effects of air pollution (Delfino et al. 2002; Galan et al. 2003; Garty et al. 1998; Gu and Rathouz 2004; Ostro et al. 1995; Villeneuve et al. 2007). Influenza epidemics have also been examined as a possible confounding factor in air pollution studies, although no evidence has been found to

suggest that flu epidemics confound observed effect of air pollution (Fauroux et al. 2000).

Treatment for asthma exacerbations

Patients with asthma are advised to have a plan, often written, to manage an asthma exacerbation at home. Recommendations include taking rescue medications (inhalers with short acting beta$_2$-agonists or SABAs), avoiding/removing the environmental trigger, and self-monitoring airway function at home using a meter. The use of a rescue inhaler more than twice a week may indicate the need for long-term control therapy (e.g. inhaled corticosteroids) (NAEPP 2007). If symptoms do not respond to use of a rescue inhaler, oral systemic corticosteroids may be initiated, often for a course of 5-10 days (McFadden 2003; Rachelefsky 2003; Rowe et al. 2004). Essentially, if the patient is sick enough to need emergency care at an emergency room or hospital, they need a course of oral systemic corticosteroids, unless use is contraindicated by other health conditions. Rescue inhalers are the first line of therapy because oral systemic corticosteroids take longer to act than rescue inhalers (hours compared with an immediate effect) and can also have serious side effects, especially if taken long term. Typically patients must contact a doctor for a single course of oral systemic corticosteroids (phone, office visit, or as part of a discharge from the ER or hospital), although it may be provided for patients to have on hand in the low percentage of asthma patients who experience life-threatening asthma exacerbations. For most people, improvement after an asthma exacerbation is quite gradual. Even when symptoms have resolved, evidence of inflammation in the airways may continue for up to 2–3 weeks (McFadden 1975).

All of the air pollution studies with a medication-based outcome have employed use of rescue medications as an outcome, typically based on the patient's diary(Gent et al. 2003; Slaughter et al. 2003) or fills (Gu and Rathouz 2004). I am not aware of previous studies that have used oral systemic corticosteroids as an outcome in an air pollution study. I use fills of oral systemic corticosteroids as an outcome in this study because the fill date is likely to be closely related in time to both the asthma

exacerbation and the actual use of the drug. In contrast, rescue medications may not be used immediately and have a weaker relationship with use of the drug and the asthma exacerbation. I can observe fills, but not actual use, in medical claims data.

Some studies have found that patients who are taking long-term control medications have weaker associations between air pollution and asthma exacerbations (Delfino et al. 2002; Hiltermann et al. 1998). This is remarkable given that use of long-term control medication is considered a marker for asthma severity. Delfino et al. conclude that severity of asthma is not a marker for the patient's sensitivity to air pollution. Asthma severity is typically defined based on use of long-term controllers, which are recommended if the asthma patient uses their rescue inhaler more than twice a week (NAEPP 2007).

Studies have generally not found evidence of threshold effects, finding health effects of air pollution even at the relatively low levels currently experienced in the U.S. (Burnett et al. 1997; Jaffe et al. 2003; Petroeschevsky et al. 2001; Tenias et al. 1998). There are a variety of reasons that threshold effects may be difficult to observe, even if processes within individuals are highly non-linear (Rothman and Greenland 1998). For example, if individuals have different thresholds for an effect (susceptibility), the observed relationship in a population would on average be linear.

The most commonly studied asthma outcomes in large-scale air pollution observational studies are emergency room visits for asthma and hospital stays for asthma (Atkinson et al. 2001; Cody et al. 1992; Galan et al. 2003; Garty et al. 1998; Gouveia and Fletcher 2000; Jalaludin et al. 2007; Kesten et al. 1995; Lin et al. 2002a; Lin et al. 2002b; Neidell 2009b; Norris et al. 1999; Schwartz et al. 1993; Villeneuve et al. 2007; Walters et al. 1994). These studies have generally found a small but statistically significant association between air pollutants and outcomes. Comparing the reported values from the studies is complicated by the fact that marginal effects of pollutants are reported for different changes in the pollutant and pollutants may be measured differently.

Air pollution studies using hospitalization or emergency room visits as an outcome typically report an odds ratio which is interpreted as a relative risk, which is approximately true when the event is sufficiently rare. Emergency room visits for asthma are relatively rare, with 8.8 annual visits per 100 people with asthma (Moorman et al. 2007). Hospital stays (measured by discharges) for asthma are even rarer, with 2.5 discharges per 100 persons with asthma annually (Moorman et al. 2007).

One of the considerations when measuring asthma exacerbations with ER visits or inpatient stays is that this type of medical care is considered to be "ambulatory care sensitive" (AHRQ). This means that appropriate preventative care and early intervention should prevent hospitalizations and emergency room visits. Nevertheless, even with appropriate care, some patients may require hospitalization, especially when a respiratory infection complicates the asthma exacerbation (Reddel et al. 1999). If low socioeconomic status is correlated with having inadequate access to preventative care and greater exposure to air pollutants, estimates of the effect of air quality may be larger than what one might observe in patients with higher socioeconomic status. Another limitation of measuring asthma morbidity by ER visits or inpatient stays is that it only captures the most seriously ill population and may be insensitive to effects that may be felt more commonly by most people with asthma. Furthermore, the threshold to admit asthma patients to the hospital may vary over time and community. A study of the severity of asthma admissions in Monroe County New York found that despite an increase in asthma severity, hospital admissions remained flat because the hospital appeared to increase the threshold at which they admitted patients in response to the increase number of asthma patients (Russo et al. 1999). This type of response by hospitals would attenuate the effects of air pollution observed in time series models of asthma hospital admissions.

One advantage of measuring asthma exacerbations by OSC fills is that OSC fills are less sensitive to availability of preventative care and measures a lower morbidity level that is more commonly experienced by patients with asthma. OSC medication is provided to both prevent patients from needing care in the emergency room and also to

aid in recovery from an asthma exacerbation after being seen in the emergency room. In the descriptive analysis, I provide some evidence (discussed in the result section), that ER visits are associated with OSC fills.

A few studies have examined the use of rescue medication as an effect modifier or outcome in air pollution epidemiological studies. A study of a small cohort of children (82) found that rescue medication use was not a confounder, but attenuated the association between particulate pollution and asthma exacerbations(Peters et al. 1997). A recent study of a Medicaid population found that SABA fills (currently the most common rescue inhaler) were strongly associated with ER visits and hospitalizations (Naureckas et al. 2005). While the authors hypothesized that SABA fills would occur prior to ER visits and hospital stays as the patient self-treated worsening asthma symptoms, the authors found that SABAS fills were more strongly related to a day or two after an ER visit or inpatient stay for asthma.

Physician office visits for asthma have been studied in a few air pollution studies (Fauroux et al. 2000; Jalaludin et al. 2004; Sinclair and Tolsma 2004). Office visits for asthma relatively common with an average of 61.2 annual office visits for asthma per 100 people with asthma(Moorman et al. 2007).

Development of asthma

Clinical evidence points to certain viral infections (particularly during infancy) and airborne allergens, in the presence of genetic factors, as the most important factors in the development of asthma (NAEPP 2007). Exposure to house-dust mites and cockroach residue are now understood to be the more important airborne allergens than pet dander(NAEPP 2007). The contribution of air pollution to the development of asthma is controversial and may be related to allergic sensitization (American Thoracic Society 2000). One study found that heavy exercise (three or more team sports) in communities with high ozone concentrations has been associated with an increased incidence in children (McConnell et al. 2002). Obesity has also been linked to higher incidence of asthma, although the causal relationship (if any) is not well understood (Ford 2005). Sex also may have a role in the development in asthma. While asthma

prevalence may be higher among young boys, by puberty, asthma prevalence rates shifts higher for women.

Air Pollutants

Air pollutants regulated by the Clean Air Acts are called criteria pollutants and include particulates (PM), ground-level ozone (O_3), carbon monoxide (CO), sulfur oxides (SO_X, especially SO_2), nitrogen oxides (NO_X, such as NO_2) and lead. In this subsection on air pollutants, I motivate the focus of this study on ozone and particulate pollution. I also briefly review basic properties of these pollutants and how they relate to the interpretation of results. Finally, I discuss measurement of air pollution exposure and the potential impact of measurement error.

This study focuses on ozone and particulate pollution because these pollutants are the most widespread health threats. Ozone is a highly reactive gas that forms from gases emitted from combustion via a reaction that is activated by sunlight. Note that ground-level ozone that is the focus of this study is distinct from the "ozone layer" in the extreme upper atmosphere that protects the Earth from harmful ultraviolet light. The "ozone layer" is understood to form from different processes and does not mix with ground level ozone.

Particulate pollution is composed of solids suspended in the air and may be formed from combustion processes (vehicles, fireplaces, commercial) as well as from dust (construction sites, commercial processes). The chemical composition of particulates varies depending on the source. It is not well understood how chemical composition of particulates may mediate or exacerbate the effect of particulates on health. Monitoring of the chemical composition of particulates is in its infancy. The EPA currently regulates the concentrations of different size classifications of particulates, fine particulates ($PM_{2.5}$) with a size <2.5 micrometers and thoracic particulates that measure <10 micrometers (PM_{10}). Larger particulates (PM_{10} and larger) may be visible as black particles (i.e. from a smoke stack) while smaller sizes ($PM_{2.5}$) are not visible but contribute to summer haze or smog. In this study, I use fine

particulates ($PM_{2.5}$) to measure particulate pollution because it is a major portion of PM_{10} and is believed to be more strongly associated with health effects. Health effects may be stronger because smaller particulates are absorbed more deeply into the lungs and bloodstream and because the smaller particulates contain more hazardous components than the larger sized particles (Trasande and Thurston 2005; Ward and Ayres 2004).

In Dallas-Fort Worth, ground-level ozone is the only criteria pollutant that exceeds current regulatory standards. In the summer, vehicle emissions are an important source of air pollution, which can contribute to both the formation of ozone and fine particulates. Vehicle emissions, especially in close proximity, are particularly harmful for asthma patients (Sarnat and Holguin 2007).

I focus on ozone and particulates instead of other criteria pollutants because the clinical evidence for short-term effects on asthma is strongest and also because they are markers for summer pollution haze from vehicle emissions, which are an important source in Dallas-Fort Worth. All of the other criteria pollutants except lead are emitted by the same processes that create ozone and fine particulates. In fact, morning NO_2 is one of the important factors used to make ozone forecasts (EPA 2003) since it is directly involved in the formation of ozone. The EPA notes that care must be taken in interpreting the effects of particulates and their relationship with other pollutants. Particulates could have an effect independent of other air pollutants; they could also be an indicator of a mixture of pollutants that originate from the same source as PM. Copollutants may mediate the effects of PM, or PM may alter the toxicity of copollutants (EPA 2008). Previous work on copollutant models have found that effects of particulates on respiratory symptoms were generally robust to inclusion of copollutants, particularly for studies limited to the warm months (Aekplakorn et al. 2003; Mortimer et al. 2002; Tolbert et al. 2007; Ulirsch et al. 2007).

This study examines data only from the warm season in Dallas-Fort Worth, May – October. Previous studies have noted the importance of controlling for seasonality when studying short-term associations between air quality and health effects(EPA

2006a; EPA 2008) due to seasonal differences in pollution sources, respiratory infections, as well as activity patterns. Ozone levels typically peak in the summer due to sunlight needed to initiate the reaction to create ozone. Particulate matter may peak in the winter due to the use of fireplaces and other combustion processes for heating.

This study treats air quality levels as exogenous, although they may be endogenously determined to an extent. For example, air quality levels tend to be better on weekends in areas such as Dallas where transportation (i.e. cars) are the primary source of pollutants. On weekends, there are fewer cars on the road and thus fewer pollutants put into the air. On expected poor air quality days (days likely to have an ozone alert), people may be less likely to run their lawnmower, which may prevent levels from reaching as high as would have otherwise. People can avoid taking unnecessary trips and filling their gas tanks in the morning to limit their contribution to poor air quality. A program in Mexico City attempted to improve air quality by limiting the use of vehicles (Davis 2008); this was also the strategy during the Beijing Olympics. The Dallas-Fort Worth Metroplex in particular has emphasized voluntary emission reductions on days when poor air quality is expected (Stuckey and Sattler 2003). An evaluation of the "Spare The Air" program in the San Francisco area found a small but measurable reduction in traffic volume and increase in use of public transportation using regression discontinuity and difference-in-difference designs (Cutter and Neidell 2009).

If people do voluntarily lower their emissions when ozone alerts are issued and air quality forecasters do not anticipate this, ozone levels will peak at lower levels and generate more "false alarm" ozone alerts. Forecasters could anticipate the emission reductions if the reductions are systematic: that is if people and businesses reduce their emissions in the same way for each ozone alert. However, voluntary emissions are likely to be difficult to predict, given that the cost of reducing emissions may vary day to day. For example, emitters may lower their emissions for a day or two of ozone alerts, but then may not be able to continue for a long ozone episode. Since actual ozone

levels, not forecasted levels, are used in the regression, the excess number of false alarms should not bias the identification of the effect of ozone alerts.

The identification of the effect of ozone alerts requires some random error in the ozone forecast. If forecasts were perfect, then there would be no false alarms or near misses needed to separate the effect of ozone alerts from ozone itself. A systematic error in forecasts, such as conservative forecasts that result in more false alarms than missed alerts might result in a lower effect of smog alerts if people pay less attention to the alerts if the alerts are perceived as being consistently wrong. However, I do not view this as bias. Rather, the ozone alert is less effective if it is perceived as being overly conservative and the effect of smog alerts is accurately estimated.

I can only separate out the independent effects of ozone and ozone alerts at ozone levels where there is variation in ozone alerts. For example, suppose ozone forecasters rarely miss issuing an ozone alert when ozone levels are very high. Beyond this level, ozone alerts are confounded with ozone levels. This would bias the association between asthma and ozone alerts away from a protective association to a harmful association at high ozone levels where there are no missed ozone alerts. Similarly, if ozone alerts are never issued at very low levels, the protective effect of ozone alerts would be biased toward finding a more protective association, in the region where there are no false alarm ozone alerts. In the results section, I examine the overlap between ozone levels and ozone alerts (Figure 4-10). No ozone alerts were issued on days with ozone levels less than 41 ppb ozone (180 days out of 1625 days, 11% of ozone season) and all days that exceed 109 ppb (16 days, less than 1% of ozone season) experienced ozone alerts.

The identification of the ozone alert effect also requires that any systematic errors in the forecast are not correlated with variables that are correlated with asthma exacerbations. Table 2-1 lists factors that contribute to ozone and fine particulate pollution and are commonly used to generate ozone forecasts. Consider temperature as an example. While higher temperatures cause increased ozone formation, very high temperatures promote increased mixing of the air, dispersing pollutants and improving

air quality. Suppose that the forecaster consistently underestimates this mixing effect of temperature and generates more false alarm ozone alerts. Then I would observe an excessive number of high temperature days on ozone alert days than would be observed if the forecast error was random. Suppose that higher temperatures are associated with fewer asthma exacerbations, because people avoid strenuous outdoor activity due to the heat. Then we would observe fewer asthma exacerbations on ozone alert days if ozone alerts were systematically correlated with lower temperatures, biasing the protective effect of ozone alerts upward. This bias can be avoided if measures such as temperature and humidity are included in the model to control for behavior related to comfort and not ozone alerts.

Personal exposure to air pollution

Exposure to air pollution is measured by monitors located within the community, called ambient pollution levels. The difference between ambient levels and personal exposure is determined by the person's activity patterns such as outdoor activities and where they work or go to school. People can lower their exposure to poor air quality by staying indoors. Ozone levels are typically very low indoors because ozone is extremely reactive with surfaces and quickly decomposes into harmless gases indoors. Ozone levels are higher around freeways, which are a source of precursor pollutants, suggesting that people who live or work in close proximity to large freeways may have higher personal exposure to ozone. Ambient monitors for ozone are placed at least 100 meters away from large roadways to ensure that monitor readings are representative of the surrounding area (EPA 2006a). Indoor exposure to particulates depends on the degree of air exchange with the outdoors and indoor sources of particulates, such as from cooking or cigarettes. Air conditioning use has been found to reduce exposure to particulates (Barn et al. 2007).

There is evidence that people respond to air quality information. One study of the attendance at outdoor public attractions in Southern California decreased on days when smog alerts were issued (Graff Zivin and Neidell 2009). The effect was the

strongest on the first day of a series of alerts and lessened during additional alert days. Patients with respiratory conditions (such as asthma) or cardiac related conditions are at the highest risk and are specifically encourage to undertake the efforts to avoid exposure. A previous study found that parents of children with asthma in Salt Lake City, Utah were more aware of air pollution advisories and limited their child's activity more than parents of children without asthma, although they did not always follow the recommendations in the advisories (McDermott et al. 2006). People can also avoid long-term exposure by choosing to live in areas with better air quality. There is some evidence that air quality may be capitalized into home prices (Chay and Greenstone 2005).

Table 2-1. Variables commonly used to forecast ozone and fine particulate levels

Phenomena	Emissions	Chemistry	Accumulation/Dispersion/Removal
Aloft Pressure Pattern	No direct impact.	No direct impact.	Ridges tend to produce conditions conducive for accumulation of PM2.5 and ozone. Troughs tend to produce conditions conducive for dispersion and removal of PM and ozone. In mountain-valley regions, strong wintertime inversions and high PM2.5 levels may not be altered by weak troughs. In addition, high PM2.5 and ozone concentrations often occur during the approach of a trough from the west.
Winds and Transport	No direct impact.	In general, stronger winds disperse pollutants, resulting in a less ideal mixture of pollutants for chemical reactions that produce ozone and PM2.5.	Strong surface winds tend to disperse PM2.5 and ozone regardless of season. However, strong winds can create dust which can increase PM2.5 concentrations. In the East and Midwest, winds from a southerly direction are often associated with high PM2.5 and ozone, due to transport from one region to another.
Temperature Inversions	No direct impact.	Inversions reduce vertical mixing and therefore increase chemical concentrations of precursors. Higher concentrations of precursors can produce faster, more efficient chemical reactions that produce ozone and PM2.5.	A strong inversion acts to limit vertical mixing allowing for the accumulation of PM2.5 or ozone.
Rain	No direct impact.	Rain can remove precursors of ozone and PM2.5.	Rain can remove PM2.5, but has little influence on existing ozone.
Moisture	No direct impact.	Moisture acts to increase the production of secondary PM2.5 including sulfates and nitrates.	No direct impact.

Phenomena	Emissions	Chemistry	Accumulation/Dispersion/Removal
Temperature	Warm temperatures are associated with increased evaporative, biogenic, and power plant emissions, which act to increase both PM2.5 and ozone. Cold temperatures can also indirectly influence PM2.5 concentrations (i.e., home heating on winter nights).	Photochemical reaction rates for ozone increase with temperature.	Although warm surface temperatures are generally associated with poor air quality conditions, very warm temperatures can increase vertical mixing and dispersion of pollutants.
Clouds/Fog	No direct impact.	Water droplets can enhance the formation of secondary PM2.5. Clouds can limit photochemistry, which limits ozone production.	Convective clouds are an indication of strong vertical mixing, which disperses pollutants.
Season	Forest fires, wood burning, agriculture burning, field tilling, windblown dust, road dust, and construction vary by season.	The sun angle changes with season, which changes the amount of solar radiation available for photochemistry.	No direct impact.

Source: Table 2-5 (page 40) from EPA guidance document on developing ozone and fine particulate forecasts (EPA 2003).

Chapter 3 Data and Methods

This section first explains data and methods. I first discuss how the main sample and asthma 2005 cohort are defined and the outcomes. I then describe the air quality and ozone alert measures and control variables. The section concludes by describing the model specifications and how these specifications test my hypotheses about ozone, ozone alerts and fine particulates. Three groups of multivariate analyses were conducted. The first and largest group of models related previous day ozone to outcomes and examined results with and without controls for ozone alerts, alternative specifications, and results by age group. The second group of models was similar but included interaction terms between ozone, ozone alerts, and fine particulates to assess whether there was a multiplicative effect of ozone alerts. The final group of models explored both past and future lags of ozone, ozone alerts, and fine particulates.

Subjects

Subjects who lived in Dallas-Fort Worth and were enrolled in a health plan that contributed data during at least 1 complete ozone season 2000-2008 were included in the main analysis.[1] Data on subjects were only available through September 2008 (October was not available) so the ozone season was limited to May-September for 2008 only. A six month run-out period was required for the claims data, which is sufficient to capture all visits or fills made during the study period January 2000-September 2008. Patients who may have switched health plans during the season or moved within the Metroplex are included. Patients who leave the employer or disenroll from the employer's health plan (i.e. enroll in their spouse's plan) cannot be followed. The 2005 asthma cohort was constructed from the subset of subjects treated for asthma

[1] Dallas counties include: Collin, Dallas, Denton, Ellis, Henderson, Hunt, Kaufman, and Rockwall. Fort Worth counties include: Hood (deleted 2003), Johnson, Parker, Tarrant, and Wise (added 2003)

in 2005 (ICD-9-CM 493) and were followed 2002-2006. The 2005 asthma cohort was constructed in 2007 when MarketScan data was only available through 2006. The 2005 asthma cohort was also limited to 2002 and later because previous versions of this study used ozone alert data from the EPA's AirNow system, which did not have data prior to 2002. The asthma cohort was selected based on enrollment in 2005 because earlier versions of this work used nationwide data from MarketScan and thus it was impossible to pull data for all asthma patients nationwide each year 2002-2006 due to the large size of the file. Asthma patients were selected in 2005 to maximize the sample size of asthma patients since enrollment was lower in earlier years. In 2009, this work was refocused on Dallas-Fort Worth because of concerns about the accuracy of the nationwide data from the AirNow program (a voluntary reporting system). Additional ozone alert data was obtained from the TCEQ and additional MarketScan data was added to include everyone enrolled in a plan and living in Dallas-Fort Worth January 2000 to September 2008.

Information on subjects and their utilization of medical care services was obtained from Thomson Reuters MarketScan Commercial Claims and Encounters database January 1, 2000-September 30, 2008, which contains millions of de-identified medical claims, including pharmacy claims and enrollment information for employees and their dependents enrolled in health plans offered by predominantly large, self-insured employers. Because the data conformed to the Health Insurance Portability and Accountability Act of 1996 (HIPAA) confidentiality requirements, the study did not require informed consent.

The number of enrollees in the main analysis varied by year from 24,615 in 2000 to a high of 427,891 in 2007. The 2005 asthma cohort included 13,687 subjects with asthma 2005.

Outcomes

There were six asthma outcomes and one non-asthma outcome used in the multivariate analysis: (1) asthma emergency room (ER) visits, (2) asthma hospital stays,

(3) outpatient office visits for asthma, (4) fills of oral systemic corticosteroids (an emergency asthma medication), (5) fills of short-acting beta-agonists (the most common rescue inhaler), and (6) outpatient office visits for diabetes.

Asthma emergency room visits and hospital stays were hypothesized to have the strongest relationship with ozone and ozone alerts since these are likely tightly linked in time to environmental triggers, such as ozone. I also hypothesize that OSC fills will be related to previous day ozone levels because OSC are not typically kept on hand by patients and so are likely to be related closely in time to asthma exacerbations that cannot be treated by standard self-care measures, rescue inhalers. Office visits and SABA fills are expected to have a weaker relationship with ozone and ozone alerts. SABAs fills typically include at least a month's worth of medications and thus do not need to be filled at each asthma exacerbation. SABA fills and office visits may be related to future lags of ozone and ozone alerts as asthma patients notice worsening symptoms during an asthma episode. SABA fills and office visits may also be related to longer past lags of ozone and ozone alerts as patients and doctors reconsider the patient's asthma self-treatment plan after a spell of asthma exacerbations, possibly precipitated by an episode of poor air quality. Outpatient office visits for diabetes were included in the study as falsification test since ozone levels should not be related to outpatient office visits for diabetes.

The first outcome was emergency visits for asthma, defined as emergency room (ER) visits or hospitalizations with asthma as a diagnosis. Since almost all hospital stays for asthma begin in the ER (asthma hospitalizations are not planned), this measure is the same as the measure of ER visits used in previous studies (Atkinson et al. 2001; Galan et al. 2003; Garty et al. 1998; Jalaludin et al. 2007; Kesten et al. 1995; Norris et al. 1999; Schwartz et al. 1993; Villeneuve et al. 2007).

The second outcome, inpatient stays for asthma, is a subset of the first outcome, defined as those hospital or emergency room visits that resulted in an overnight stay. This outcome is equivalent to the hospital discharge measure used by other studies (Cody et al. 1992; Gouveia and Fletcher 2000; Lin et al. 2002a; Neidell 2009b; Walters et

al. 1994). For both ER visits and hospitalizations, I searched all diagnosis fields for an asthma diagnosis to ascertain if the visit or stay was for asthma. Inpatient stays had up to 15 diagnosis codes and emergency room visits had up to 2 diagnosis fields. Emergency room and hospital visits were defined using standard provider codes.

The third outcome was outpatient doctor visits for asthma. This was defined based on standard provider codes and only visits where asthma was the primary diagnosis were included.

The fourth and fifth outcomes were outpatient prescription drug fill of asthma medication, based on National Drug Codes (NDC). These codes were found by searching the Redbook™ database that provides a crosswalk between drug names and classes and NDC. All drug names listed in the NAEPP treatment guidelines were included. All claims paid by the medical or drug plan were included, regardless of whether the prescription was filled in a retail on mail-order pharmacy.

For fills of oral systemic corticosteroids (OSCs), the fourth outcome, a confirmatory asthma diagnosis was required because OSC may be provided to treat other conditions beyond asthma. Steroids control inflammation and suppress the immune system so may be used to treat autoimmune diseases and serious allergic reactions such as rheumatoid arthritis, ulcerative colitis, psoriasis, eczema or poison ivy (Brody 2009). OSCs are systemic in the sense they affect multiple body systems, not just the lungs and respiratory system. For the main analysis, a confirmatory asthma diagnosis code was required in the same calendar year as the OSC fill. Since OSCs are typically given in response to an asthma exacerbation, this measure is expected to capture most OSC fills for asthma. Since all subjects in the asthma 2005 cohort have asthma, a confirmatory asthma diagnosis was not required.

The fifth outcome was fills of short-acting beta-agonists (SABAs), the most common reliever medication and taken using an inhaler. Since these rescue inhalers are targeted to the respiratory system and are almost exclusively used to treat asthma, a confirmatory diagnosis was not required.

A final drug measure, long-term controllers, was examined in the descriptive analysis but was not included in the multivariate analysis. Long-term controllers are typically prescribed for daily use in asthmatics who have frequent asthma symptoms, indicated by using their rescue inhaler more than twice a week (NAEPP 2007). I examine long-term inhaled use descriptive since use may attenuate the observed association ozone and treatment for asthma exacerbations. I do not examine controller using the multivariate models because controller fills are expected to only weakly be associated in time with asthma exacerbations. Since controllers are inhaled medications used solely to treat breathing difficulties, a confirmatory asthma diagnosis was not required. Most controllers (commonly long-acting beta-agonists and inhaled corticosteroids) are prescribed to treat asthma, although asthma can be difficult to distinguish from COPD (chronic obstructive pulmonary disease) in older populations and is treated with some of the same drugs.

Only ozone seasons during which the subject was enrolled in a health plan and lived in the Dallas-Fort Worth Metroplex the entire season were included in the multivariate analysis. If the subject lived in the Metroplex only for part of the season, that season was excluded. For the drug outcomes, subjects were required to also be enrolled in a drug plan for the entire ozone season to be eligible for the drug analysis. For the purpose of calculating the annual rate of each outcome, all visits, fills or stays during the year were counted (not just those during the ozone season). This was done so that annual rates could be compared with rates found nationwide to assess the representativeness of the sample.

Air quality and alerts

Information on ozone alerts issued in the Dallas-Fort Worth Metroplex was obtained directly from the Texas Commission on Environmental Quality (TCEQ). Dallas-Fort Worth Metroplex uses and alert and warning system that works similar to a tornado watch and warning system (Stuckey and Sattler 2003). An ozone alert indicates

that conditions are favorable for ozone levels to exceed certain health thresholds set by the EPA (EPA 2006b). An ozone warning is issued in real-time and indicates that ozone levels have actually exceeded thresholds. Ozone alerts in Dallas-Fort Worth are issued the day before the expected poor air quality. Unlike other areas (such as Southern California), a continuous version of the ozone forecast is not issued, only alert levels. Alerts may be issued for orange (unhealthy for sensitive groups), red (unhealthy) or purple (very unhealthy) levels of ozone in the Dallas-Fort Worth Metroplex. Alerts are not issued for fine particulates in Dallas-Fort Worth. Table 3-1 shows the health advisory for each alert and the level of ozone and fine particulates associated with each alert. There is one additional alert level (hazardous) that is not shown in the Table since it rarely occurs at ambient levels in the U.S. Orange alerts are the most common alerts in the Dallas-Fort Worth Metroplex. In the primary analysis, alerts are measured by two indicator variables: orange alert and red or higher alert. In the secondary analysis, alerts are measured as orange or higher alert level. Starting in the 2008 ozone season, thresholds for each alert was lower. Prior to 2008, orange alerts were issued on days when ozone levels were expected to exceed 85 ppb using the 8-hour daily maximum measurement. This threshold was lowered to 76 ppb for the 8-hour maximum in 2008.

Hourly time-series data for ambient ozone were obtained from the EPA's Air Quality System Database (AQS) [2] for monitors in counties included in the Dallas-Fort Worth Metroplex. Fine particulate levels were reported as the average concentration in $\mu g/m^3$ over 24 hours. For ozone, the 8-hour maximum was calculated for each day based on hourly readings reported in the AQS system. I measure ozone using the 8-hour maximum because this is the measurement used for regulatory standards (National Ambient Air Quality Standards (NAAQS)) and the 8-hour maximum may also be more representative of personal exposure than a 1-hour max. The daily 8-hour maximum is the highest 8-hour average based on a running 8-hour average for days when at least 75% of the hourly readings are available (McCluney 2007). Both 8-hour and 1-hour maximum measurements have been used in previous studies with little evidence to

[2] http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdata.htm

indicate one measure is superior to the other. In Dallas-Fort Worth, the 8-hour alert threshold is surpassed much more frequently than the 1-hour threshold and thus is the measurement that triggers most air quality alerts.

For each day, the highest monitor reading in the Metroplex was used to measure that day's air quality. I used this approach because a Metroplex-wide measure is likely to be more representative of personal exposure than county-level measures since people travel within the Metroplex. Furthermore, the TECQ uses this method when reporting summary data on air quality and when issuing alerts in Dallas-Fort Worth. Also, using the Metroplex-wide measure resulted in more complete data than county-level measures since not all counties had monitors the entire study period. Other studies have assigned exposure to individuals use finer levels, such as Zip Code (Neidell 2009b) and county (Dominici et al. 2006), but these have studied more geographically diverse areas where one would expect to find important small-scale variations in air quality and weather. Dallas-Fort Worth does not have substantial geographic variation (mountains, valleys, bay) that would lead to important differences in weather or air quality by Zip Code or county.

Weather

Daily readings from weather stations in counties within the Dallas-Fort Worth Metroplex were obtained from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA). These data include daily measurements of average, minimum and maximum temperature, dew point, wind speed, precipitation and indicators for storms (hail, thunder, funnel cloud or tornado). No funnel clouds or tornados were reported during the study period. Relative humidity was constructed from dew point. Maximum daily temperature is strongly correlated with ozone formation and wind speed is correlated with fewer pollutants due to dispersion and transport of the pollutants. Relative humidity is often used as a proxy for cloud cover in ozone forecasting (EPA 2003). Precipitation is associated with clearing

out of accumulated fine particulate pollution has little impact on ozone levels (EPA 2003).

Apparent temperature was constructed from dew point and average daily temperature. Apparent temperature is designed to measure how comfortable it is to be outdoors (Rothfusz 1990; Steadman 1979) and has been used in several studies of the health effects of temperature and air pollutants (Basu et al. 2008; Medina-Ramon et al. 2006; Zanobetti and Schwartz 2005), although average daily temperature is the typical measure for this literature. The apparent temperature equation, shown in Equation 1, is based on human studies of comfort (Steadman 1979). In the equation, T is temperature in degrees Fahrenheit and R is relative humidity as an integer percentage (0 to 100).

Equation 1. Apparent temperature (A) or heat index equation

$$A = -42.379 + 2.04901523 * T + 10.14333127 * R - 0.22475541 * T * R - 6.83783 * 10^{-3} * T^2 - 5.481717 * 10^{-2} * R^2 + 1.22874 * 10^{-3} * T^2 * R + 8.5282 * 10^{-4} * T * R^2 - 1.99e^{-6} * T^2 * R^2$$

In most of the analyses, a second order function of temperature and relative humidity was included that is intended to approximate the functional form of apparent temperature and allow the data to determine the coefficients on each term. The functional form is shown in Equation 2.

Equation 2. Polynomial of temperature and relative humidity

$$T + T^2 + R + R^2 + (T * R) + (T * R)^2$$

Some specifications also included controls for the change in temperature and relative humidity from the previous day, because some recent work indicates that changes in weather may be more important to asthma exacerbations in children than their actual levels (Mireku et al. 2009).

The final set of control variables were indicators for day of week, federal holidays (Memorial Day, Labor Day, and July 4th), and weekends. The primary analysis (general sample) also included indicators for month. Previous work has demonstrated that asthma exacerbations, especially among school-aged children, are much higher in

September, possibly precipitated by viral infections that tend to occur when school returns to session in the fall (Johnston et al. 2006).

Descriptive Analysis

Before turning to the multivariate models, I describe the subjects, outcomes, ozone levels, alerts and some of the interactions between these factors. I describe sample characteristics, including the general types of health plans that subjects are enrolled in and the fraction of subjects that also have drug coverage. Asthma prevalence rates are presented, although these must be interpreted as the prevalence of asthma treatment, not true prevalence, since true prevalence is not observable in medical claims records, without a medical history or other information. Medical claims data can capture the prevalence of treatment for asthma and must be defined over a specified time period. For the purpose of this study, asthma treatment prevalence is defined annually as the number of people treated for asthma during a calendar year. I report annual rates of visits, fills or stays per 100 people with asthma using this definition of asthma. I also report annual rates per 1,000 in the general population.

In the sub-analyses by age group (prevalence and outcome rates and some models), I have defined children as age 5-19 and adults age 20-54. I limited the sample of children to age 5 and older because asthma can be difficult to distinguish from wheezing that is relatively common in young children but often does not develop into asthma (Litonjua and Weiss 1997). In medical claims data, an asthma diagnosis is likely to occur as a rule-out diagnosis and may not indicate asthma. I limit the analysis of adults to under age 55 because COPD and asthma can be difficult to distinguish in older adults. These specific cutoff, age 5 and 54, are commonly used in claims-based asthma measures, such as HEDIS.

I also explore the episodic nature of treatment of asthma by relating OSC and SABA fills, office visits and inpatient stays to ER visits in time. I take the sample of 3,735 ER visits by subjects enrolled in drug benefits during the ozone seasons and calculate the number of those visits that had a fill, visit or stay within 15 days before and after the

ER visit. This is similar to a previous study that related asthma ER visits with SABA fills, although the previous study reported odds ratios and stratified by subject (to address subject-level heterogeneity), seasonality, and use of long-term controller methods using Mantel-Haenszel methods (Naureckas et al. 2005).

Model specification and inference

I conducted three general types of analyses that examined the association between ozone, ozone alerts and outcomes: (1) previous day models without air pollution-alert interactions, (2) previous day models with air pollution-alert interactions, and (3) multiple lag models (lag -3 to lag +3).

Previous day models without pollution-alert interactions

For the previous day models, I explored several different specifications. For the first group of previous day models, I compared results with and without ozone alerts to assess if ignoring information about ozone alerts biased the ozone-asthma association. I also compared models with and without controls for fine particulates to assess if fine particulates appeared to confound or modify the association between ozone and asthma exacerbations. In this first group of previous day models, I included controls for weather, day of week, Federal holidays and month. Weather was measured with the polynomial of temperature and humidity shown in Equation 2, the change in temperature and humidity from the previous day, precipitation (inches) and indicators for extreme weather. The final variable in the specification controlled for the size of the sample each ozone season since it varied year to year. Since not all subjects were enrolled in drug benefits, the number of subjects eligible is smaller for the drug outcomes than for the visit or hospital stay outcomes. Only days in the ozone season (May-October) were included in all specifications. This first group of models used the entire sample (general at risk sample).

In these models, I expect a positive association between ozone and asthma outcomes, meaning that increases in ozone levels are associated with increasing asthma symptoms. I expect a negative association with ozone alerts since subjects susceptible

to air pollution are hypothesized to be aware of ozone alerts and avoid exposure. Thus personal exposure to poor air quality is expected to be lower on ozone alert days that it would have been without the alert, for those subjects who are aware of the alerts and modify their behavior by staying indoors and avoiding outdoor exercise. I expect that excluding ozone alerts from the models will attenuate the association between ozone and asthma exacerbations because actual personal exposure to air pollution will be systematically lower than on similar days without an ozone alert, for subjects who respond to the health information contained in an ozone alert. I also compared models of outcomes for children and adults. I hypothesize that children may be more sensitive than adults to ozone levels, as found in clinical studies. Since there is a greater potential for harm from ozone for children, I would also expect children (or their caregivers) to have a stronger incentive to respond to ozone alerts. This would be observed as a larger protective (more positive) association between ozone and asthma outcomes for children and also a larger harmful (more negative) association between ozone alerts and asthma outcomes for children.

The next set of previous day models explored alternative specifications using outcomes from all age groups. First, I assessed the impact of excluding the first and last two years of data, which were not available for the 2005 asthma cohort analysis and also happened to experience lower ozone levels. I then explore alternative specifications of weather using apparent temperature and temperature and humidity without the interaction terms shown in Equation 2. The sensitivity of results to the specification of weather is important to explore because ozone is positively correlated with temperature due to the fact that strong sunlight drives the hot summer days and also the reactions that forms ozone from precursor pollutants. People may also stay indoors when it is uncomfortable outside (measured by apparent temperature), which would make higher temperature and humidity negatively correlated with personal exposure to ozone and attenuate associations between ozone measured at community monitors and asthma exacerbations. I also estimate models with and without controls for month. Typically the epidemiological literature includes monthly controls for

seasonality, often as part of complex functions. Asthma ER visits peak in September due to the prevalence of respiratory infections that occur when children return to school. Ozone levels also vary monthly, generally higher in July and August due to stronger sunlight and longer days. The final sensitivity analysis uses the 2005 asthma cohort instead of the general at risk sample in the main analysis. In the 2005 asthma cohort, alerts are measured by a single variable, orange or higher ozone alerts. In the main analysis, alerts are measured by two variables, orange alerts and red or higher alerts.

I focus the main analysis on previous day ozone and ozone alerts because short lags (previous or same day) have been shown to be the most important lags for studies of asthma ER visits and inpatient stays (EPA 2006a; EPA 2008).

For the general sample, a daily time series of the number of visits, fills or stays each day was constructed for May-October of each year (except September 2008 which was not available). The number of visits, fills or stays was predicted as a function of air pollution, alerts, and control variables using a count model, typically the negative binomial model, implemented with nbreg in STATA© version 10. The negative binomial model allows for overdispersion. In some of the specifications of inpatient stays, the negative binomial could not be estimated so the simpler poisson model was used instead, implemented using the poisson command in STATA.

In both types of count models, the exponentiated coefficients represent the relative risk for a marginal change in the variable, except for variables that have an interaction term (temperature and humidity). For variables that are not interacted, I can infer percent change in the outcome associated with a change in that variable. Results are presented as the percent change in visits associated with a 20 ppb increase in 8-hour ozone levels and a 10 $\mu g/m^3$ increase in fine particulate levels. For reference, a 20 ppb increase in 8-hour ozone is about 24% of the orange alert threshold and a 5 $\mu g/m^3$ in fine particulates is about 13% of the orange alert threshold. The threshold for ozone alerts was 85 ppb prior to 2008 and 76 ppb in 2008. For fine particulates, the threshold for an orange level alert would be 40 $\mu g/m^3$, if these types of alerts had been issued in study area (they are not issued in Dallas-Fort Worth). 95% confidence

intervals were calculated for the percent change in visits or fills using the delta method, implemented using the prvalue command in STATA. Since the transformed coefficients and the delta method produced almost identical point estimates, I report model inference using the delta method for both the point estimates and confidence intervals. Coefficients and standard errors for each model are presented in Appendix A (page 115). The epidemiological literature typically reports the association between air quality and outcomes as the relative risk or odds ratio associated with a change the size of the interquartile range or some fixed value, such as 10 μg/m^3 fine particulates and 10 ppb ozone (EPA 2006a; EPA 2008).

The 2005 asthma cohort was analyzed by constructing a daily time series for each individual with asthma for May-October of each season 2002-2006. The probability of having an outcome was modeled using a logit model and standard errors were adjusted for clustering of observations within patients. The interpretation of model coefficients in the logit model is similar to the count models. I used the mfx command in STATA to estimate the point estimates and 95% confidence intervals for a 1 point change in ozone, fine particulates or alerts, and then transformed the point estimate and confidence intervals into a 20ppb increase in ozone and a 10 μg/m^3 increase in fine particulates, similar to the approach described above.

Previous day models with pollution-alert interactions

The second general type of analysis interacted previous day ozone, ozone alerts, and fine particulates, shown in Equation 3. Oz stands for Ozone, PM stands for fine particulates, Orange represents orange level ozone alerts (unhealthy for sensitive groups) and Red represents red or higher level ozone alerts (unhealthy to very unhealthy).

Equation 3. Air pollution-alert interaction terms

$$Oz + PM + Orange + Red + (Oz * Orange) + (Oz * Red) + (PM * Orange) + (PM * Red) + (Oz * PM) * (Oz * PM * Orange) + (Oz * PM * Red)$$

The control variables are the same as the first set of models in the previous day models, with weather measured on the previous day. The previous study of ozone alerts

(Neidell 2009b) did not explore interactions between ozone and ozone alerts. My hypothesis is that ozone alerts on days with worse air quality may be observed to be more protective. This would occur because ozone alerts on low ozone days may not make much difference, simply because the level of harm from ozone is relatively low. But at higher ozone levels, one can lower one's personal exposure to poor air quality by staying indoors. Furthermore, since people can obtain information about current ozone levels in real time, people may also make more of an effort to heed ozone warnings when they observe that high levels have already been achieved during the day. The TCEQ provides information to news and media outlets (warnings) when actual ozone levels have exceeded thresholds and people can also check the current air quality on-line.

Inference regarding the association between ozone, ozone alerts, and outcomes is complicated by the interaction terms because now marginal effects may vary at different points in the distribution. For example, the interaction terms allow ozone alerts to have different effects so that ozone alerts may not be protective at low ozone levels but could be protective at high ozone levels. It has been shown that for non-linear models, individual coefficients on interacted terms may not reflect the true sign, magnitude, nor statistical significance of the relationship (Ai and Norton 2003). I avoid this problem by using the estimated model to predict the number of visits, stays or fills at a range of values for ozone, fine particulates and ozone alerts. I predict the percent change in outcomes associated with an increase in ozone levels from 70 to 90 ppb and an increase in fine particulates from 15 to 25 $\mu g/m^3$. I estimate the effect of these increases on days with and without an ozone alert. Each of the predictions are made using each observation in the data, rather than sample means, since the sample mean may not represent a typical day, given non-linearity in the relationships and the count model. In the predictions, I change each of the interaction terms as well as the main terms to fully capture the non-linear effects. I construct 95% confidence intervals using bootstrap methods with 10,000 repetitions. Confidence intervals are constructed using the percentile method and bias corrected using STATA's -estat bootstrap- command.

I also present results from the interaction models graphically as a dose-response relationship where the dose is the concentration of ozone or fine particulates and the response is the number of visits, fills or stays. The dose-response relationship is presented for days with and without ozone alerts. The graphs are generated by predicting outcomes at various levels of ozone and fine particulates and turning on and off the ozone alert variables. As before, predictions are made at the individual level for all observations, rather than at sample means.

Multiple Lag Models

The final group of models related past lags (lags -1 to -3), current values (lag 0) and future lags (lag +1 to lag+3) of ozone, fine particulates and ozone alerts to outcomes. For asthma inpatient stays and ER visits, I hypothesize that previous day or same day lags of ozone and ozone alerts have the strongest association with outcomes since the harmful effects of ozone are experienced very quickly during and after exposure to elevated levels of ozone. Future lags of ozone and ozone alerts may be important for the drug fill outcomes if subjects form expectations about the future and fill medications in advance of expected poor air quality days. Past lags (lags -2 and -3) may be important to office visits if subjects seek medical advice and/or adjust or refill their medications after asthma exacerbations triggered by poor air quality. The multiple lag models control for weather using the same lags (-3 to +3) as air pollution and ozone alerts. Weather is modeled using apparent temperature to save parameter space and the same measures of precipitation and severe weather as before. Also included are controls for Federal holidays, month, day of week and the number of subjects in each ozone season. Inference for the lag models is the same as the previous day models without interactions.

Table 3-1.Ozone alert levels and health advisory

Level	Ozone			Particulate matter	
	8-hour		1-hour	$PM_{2.5}$ (24-hour)	PM_{10} (24-hour)
	Pre-2008	2008	No change	No change to standards during study period	
Good	0-64 ppb	0-59 ppb	Not reported.	0-15 µg/m³	0-50 µg/m³
	None			None	None
Moderate	65-84 ppb	60-75 ppb	Not reported.	15-40 µg/m³	50-150 µg/m3
	Unusually sensitive individuals may experience respiratory symptoms.			Respiratory symptoms possible in unusually sensitive individuals, possible aggravation of heart or lung disease and premature mortality in people with cardiopulmonary disease and older adults.	
Unhealthy for Sensitive Groups	85-104 ppb	76-95 ppb	125-164 ppb	40-65 µg/m³	150-250 µg/m3
	Increasing likelihood of respiratory symptoms and breathing discomfort in active children and adults and people with lung disease, such as asthma.			Increasing likelihood of respiratory symptoms in sensitive individuals, aggravation of heart or lung disease and premature mortality in people with cardiopulmonary disease and older adults.	
Unhealthy	105-124 ppb	96-115 ppb	165-194 ppb	65-150 µg/m³	250-350 µg/m3
	Greater likelihood of respiratory symptoms and breathing difficulty in active children and adults and people with lung disease, such as asthma; possible respiratory effects in general population.			Increased aggravation of heart or lung disease and premature mortality in people with cardiopulmonary disease and older adults; increased respiratory effects in general population.	
Very	≥125 ppb	116-404 ppb	195-404 ppb	150-250 µg/m³	350-420 µg/m3

Level	Ozone			Particulate matter	
	8-hour		1-hour	$PM_{2.5}$ (24-hour)	PM_{10} (24-hour)
	Pre-2008	2008	No change	No change to standards during study period	
Unhealthy	Increasingly severe symptoms and impaired breathing likely in active children and adults and people with lung disease, such as asthma; increasingly severe respiratory effects likely in general population.			Significant aggravation of heart or lung disease and premature mortality in people with cardiopulmonary disease and older adults; significant increase in respiratory effects in general population	

Chapter 4 Results

In this section, I first describe the data, including patients, outcomes, and air quality. Next I describe results from the multivariate regressions of the relationship between air pollutants and asthma exacerbations.

Patients and Outcomes

Results Tables

Table 4-1 describes characteristics of subjects included in the study. The sample was evenly split by gender (47.7% male in 2007 to 52.4% in 2000). Children under 18 were the largest age group, comprising from 27.0% (2007) to 30.9% of the sample (2000). The types of health plans subjects were enrolled in varied greatly over the study period, due to new employers with different health plan offerings entering the sample as well as changes to the health plans offered at existing employers. In 2000, over half of subjects were enrolled in capitated POS (Point Of Service) plans while by 2008, an insignificant number of subjects were in POS plans. In 2007, the year of the largest sample, subjects were primarily enrolled in Preferred Provider Organizations (PPO) plans (61.9%), Health Maintenance Organization (HMO) plans (16.5%) and non-capitated Point of Service (POS) Plans (11.3%). It is difficult to interpret changes in the share of subjects who were enrolled in plans held by an employee who was salaried, since the share of subjects missing this information varied greatly (73.6% were not classified as salaried or hourly in 2007 while only 21.6% were not classified in 2000). Subjects were typically enrolled in plans that were not union negotiated; union negotiated plans accounted for 7.1% - 25.4% of subjects.

The prevalence of treatment for asthma (presence of an asthma diagnosis during a calendar year) varied from 3.0% to 4.3% with an average of about 3.9% 2000-2008 (Table 4-2). In 2000, 871 subjects were treated for asthma, which implies an asthma prevalence rate of 3.54 per 100 in the general population. Most subjects were enrolled in a drug plan on average (81.3%), although this varied from 66.3% (2006) to 98.1% (2001). Subjects treated for asthma were less likely to be enrolled in a drug plan, with average enrollment of 71.5%, about 10 percentage points less than the general population. This suggests that patients with asthma may have been enrolled through employers who offered less generous benefits and/or had lower incomes so may not have been able to afford drug coverage. The prevalence of asthma treatment was higher among children (5.2 per 100) than for adults (2.6 per 100), shown in Table 4-3. The highest asthma treatment prevalence rates were observed in 2007. Adults and children were enrolled in the drug plans at similar rates (82%).

Hospital stays for asthma was the least common outcome, with an average of 1.33 per 1,000 in the general population and 3.40 per 100 asthmatics 2000-2008 (Table 4-4). Similar to the previous tables, asthmatics were defined as subjects treated for asthma during that year. ER visits were more than twice as frequent as hospital stays, with 2.79 ER visits per 1,000 subjects in the general population and 7.13 per 100 asthmatics. Office visits for asthma were relatively common; there were 23.27 visits per 1,000 in the general population on average and 59.44 per 100 subjects treated for asthma 2000-2008. The most common quick relief medication, short-acting beta-agonists (SABA), was filled at a rate of 63.83 per 1,000 enrollees and 186.29 per 100 subjects currently treated for asthma. Oral systemic corticosteroids (OSC), an emergency medication, were filled at a rate of 11.20 fills per 1,000 in the general population and 32.68 fills per 100 among subjects with asthma. The years with the highest rates varied. ER visits, inpatient stays and doctor office visits for asthma were at the highest in the general population in the more recent years (2007-2008). SABA fills (relievers) was highest in 2001 (77.08 per 1,000) and lowest in 2008 (53.03 per 1,000).

The fill rate of long-term controllers (inhaled corticosteroids and LABAs) peaked in 2005 in the general population, which was also the year with the highest rate of OSC fills.

Inpatient stays occurred at a higher rate among adults than children while ER visits occurred more frequently among children. Adults age 20-54 had 1.33 inpatient stays per 1,000 subjects compared with 0.92 per 1000 for children age 5-19 (Table 4-5). The difference was even more striking for those with asthma since asthma is more prevalent in children. Adults with asthma had almost three times the number of inpatient stays as children with asthma. Children had 4.63 ER visits per 1,000 subjects while adults had less than half the rate (2.02 per 1,000). The rate of ER visits was more similar when only adults and children with asthma were considered. Children with asthma had 1.15 times more ER visits than adults with asthma. Similar results were found for the other asthma outcomes with children using services at a higher rate than adults, but these rates did not differ as much when comparisons were made among those with asthma. Diabetes office visits were more common for adults than children and even more frequent among adults with asthma, consistent with evidence that obesity is a contributing factor in both asthma and type 2 diabetes.

Outcomes were not evenly distributed during the 1,625 days in the ozone season May 2000 through September 2008; 24% of days did not have any ER visits and 45% of days did not have any inpatient stays (Figure 4-1). A few days had large numbers of ER visits, 1 day had 16 ER visits (10/22/2006) and 3 days had 14 ER visits (5/3/2007, 9/3/2007, 9/4/2007). Of the 60 days with 10 or more asthma ER visits, all but two of those days occurred in 2006 (19) or 2007 (39). All but eight of the days with 5 or more asthma inpatient stays occurred in 2006 (52) or 2007 (65). 48% of days had less than 10 asthma office visits and 40% of days had less than 10 diabetes office visits (Figure 4-2). Note that that each bar in Figure 4-2 represents 10 visits so the first bar is 0-9 visits. About one third of days during the ozone season had 0-4 OSC fills (Figure 4-3). About 16% of days had 10-19 SABA fills, the most common number of daily SABA fills (Figure 4-4). Note that the distributions for inpatient stays, ER visits, and OSC fills fit the

distribution assumed in the negative binomial count model. SABA fills may be better described by the poisson distribution.

The next two tables compares subjects in the main analysis with subjects in the asthma-only subsample, called the "2005 asthma cohort" because they were defined based on an asthma diagnosis in 2005. The 2005 asthma cohort had a 71% higher rate of asthma ER visits per 100 subjects with asthma (12.19 in the asthma cohort vs. 7.13 in the main analysis (Table 4-6). The ER visit rate per 1,000 in the general population was 9%-15% higher, depending on what prevalence rate was used to convert the rate per 100 with asthma to the rate per 1,000 general population. For inpatient stays, the rate per 100 with asthma was very similar in both samples, but the rate per 1,000 in the general sample (1.33 per 1,000) was much higher than in the 2005 asthma cohort (0.92 per 1,000). The 2005 asthma cohort also had a higher use of asthma outpatient visits per 100 and a higher rate of OSC fills per 100 with asthma. The reason that the rate per 100 and the rate per 1,000 yield different conclusions about the two samples is that the rates are calculated over different time periods. In the main analysis, to be counted in the rate per 100 with asthma, both the visit, stay or fill and an asthma diagnosis all occur in the same year. For the 2005 cohort, they must have an asthma diagnosis in 2005, but they could fill a drug in 2004 but not see a doctor for asthma in 2004. This fill in 2004 would count in the rate per 100 with asthma in the 2005 cohort analysis, but not in the rate per 100 in the main analysis. For the main analysis with the general sample, I require a confirmatory asthma diagnosis (within the same calendar year) on all OSC fills since OSCs may be prescribed for a variety of conditions beyond asthma. For the analysis of the 2005 cohort, I did not require a confirmatory asthma diagnosis on OSC fills since everyone in the sample had asthma.

Since use of long-term controller asthma medications may be an effect modifier, I also examined the use of these medications over time in the main sample and the 2005 asthma cohort, shown in Table 4-7 for only subjects enrolled in a drug plan. The top panel shows the use of controller medication among subjects who did not have any asthma diagnoses recorded in their data, possibly because they were enrolled for only a

year and thus had a short-time frame during which they could be treated for asthma. Since asthma controllers are not typically prescribed for other conditions, it is likely that those subjects who filled a controller probably did have asthma, even though they did not have an asthma diagnosis in their claims record, about 8.4% - 9.6% of those without an asthma diagnosis. 33%-43% of subjects with an asthma diagnosis at some point but not in the 2005 asthma cohort filled a controller in any given year. On average, 39.7% of patient-years in this sample had one or more fills of an asthma controller. In this table, the asthma diagnosis could have occurred at any point during the study (except 2005), not necessarily in the year of the controller fill. The 2005 asthma cohort (bottom panel of Table 4-7) was most likely to have fills of asthma controller medications. Each year 2002-2006, 45.6% to 62.6% of subjects in the 2005 asthma cohort filled a controller medication, for an average of about 55% over all of the patient-years 2002-2006.

Utilization of care for asthma often occurred in episodes for each subject. Figure 4-5 graphs asthma care within 15 days before and after the ER visit. The number of days since the ER visit is the horizontal axis; negative numbers indicate days prior to the ER visit and positive number indicate days after the ER visit. Some of those ER visits resulted in inpatient stays (130 on the same day or day following the ER visit). ER visits were also clustered together with some patients having an ER visits two days in a row. 95 of the ER visits also had an ER visit on the previous day.

A large number of ER visits were associated with an OSC fill on the same day as the ER visit (741) or the day after the ER visit (390). These OSC fills on the same day or day after an ER visit represented 7.4% of all the OSC fills during ozone season (out of 15,294 OSC fills). SABA fills, the most common rescue inhaler, was also frequently filled on or around ER visits. 26% (989) of the ER visits had a SABA fill on the day before, same day or day after an ER visit. Higher numbers of office visits occurred immediately after an ER visit, not before.

Ozone Forecasts, Air Pollution and Weather

Forecasts were generally accurate, with 80% of more days during the ozone season correctly forecast as high ozone days (orange alert or higher) or moderate/good days, shown in Table 4-8. The most ozone alerts were issued in 2005 (59) and 2000 (58) while 2008 had the fewest (31), despite the lower ozone alert thresholds that were implemented in 2008. 2000 and 2005 also had the most days that actually exceeded thresholds (36 days in 2000, 37 in 2002, and 44 in 2005). The most red level alerts occurred in 2000 (19) and 2002 (16) with very few red alerts in recent years (2006-2008 had a total of 9 over the 3 years). Only one purple level alert (very unhealthy) was issued in 2003. Alerts were issued conservatively, with more false alarms than missed days. Most days that actually exceed the thresholds had an alert issued, with 75%-93% of target days correctly forecasted prior 2008, but only 50% in 2008. On alert days (days forecasted to exceed thresholds), typically half of those days actually exceeded thresholds (47%-59% in each year), except for 2006 when 78% of alert days actually exceeded thresholds.

Ozone alerts were often issued for several days in a row. Figure 4-6 presents a calendar showing the ozone season each year 2000-2008. A 3 (pink) indicates that an alert was issued and the target value was achieved on that day, a 2 (yellow) indicates that no alert was issued but target values were achieved (i.e. missed alert) and a 1 (green) indicates that an alert was issued by levels did not exceed target value (i.e. false alarm). So groups of 3's and 1's represent spells where alerts were issued multiple days in a row and groups of 3's and 2's indicate days in a row of high ozone levels. In 2005, most of the 59 alert days occurred during stretches of 3 days or more when alerts were issued. Only 9 alerts were issued as a single day or two days in a row, the rest occurred as part of groups of 3 or more days in a row. Red level alerts are outlined with dashed lines and the day with a purple alert is circle with a double line.

Levels of ozone and fine particulates varied each year, shown in Figure 4-7 and Figure 4-8. The squares (green) indicate the maximum values reached each ozone season and the X (red) indicates the minimum value each ozone season. The average for the ozone season is shown by the blue dot, with error bars showing the interquartile

range of values. 2005 had the highest average ozone levels during the ozone season with an average of 69 ppb. The interquartile range included the orange alert threshold (dashed line) in all years prior to 2007, but not in 2007 and 2008 (Figure 4-7). While Dallas-Fort Worth occasionally experienced fine particulate levels in excess of the orange alert threshold, most days were below the threshold of 40 $\mu g/m^3$. Note that alerts are not issued for fine particulates in Dallas Fort-Worth (only ozone) so the 40 $\mu g/m^3$ threshold is only for reference.

Table 4-9 describes average levels of air quality and weather during the ozone seasons 2000-2008 and shows the mean, minimum, maximum, interquartile range (IQR), 25^{th} and 75^{th} percentiles, and number of observations. There were 1,625 days in the ozone season (through September 2008) and four 4 missing days were missing fine particulate data and 8 days were missing weather data, leaving a total of 1,613 days with complete data available for the multivariate analysis. Ambient ozone levels were 73 ppb during the ozone seasons 2000-2008. Fine particulate levels were relatively low (mean of 14.5 $\mu g/m^3$) , compared with the alert threshold of 40 $\mu g/m^3$, although Dallas-Fort Worth did experience a few high fine particulate days that reached up to 56.7 $\mu g/m^3$.

Average daily temperature was 80.1 °F with 50% of the days between 75 and 85°F (Table 4-9). Relative humidity averaged 73% with an interquartile range of 66 to 80%. The interquartile range for daily precipitation ranged was 0.16" to 0.45", with a high of 5.67" in 2004. Apparent temperature was typically higher than temperature due to the humidity levels (Average apparent temperature of 85.6°F). The correlation coefficient between temperature and apparent temperature was 0.97 ($p<0.001$). 38% of days during the ozone season experienced hail or thunder. Equation 4 shows the relationship between temperature (T), relative humidity (H), and apparent temperature (A), from a regression of temperature and humidity on apparent temperature. The Adjusted R^2 from this regression was 0.9997, indicating an almost perfect fit.

Equation 4. Regression of temperature and humidity on apparent temperature

$$A = 1.96 * T - 0.072 * H - 0.0088 * T^2 + 0.0013 * H^2 - 0.0026 * TH + 7.25e^{-7} * (TH)^2 - 29.60$$

Figure 4-9 shows the correlation between lags of ozone and fine particulates. All correlations were positive, indicating that ozone, fine particulates, and their lags all move in the same direction. All correlations were statistically significant at 99% confidence levels except for one, which was significant at 95% levels. The upper left quadrant shows correlations between ozone and its lags -4 to +4. The lower right quadrant shows the same for fine particulates. The lower left quadrant shows correlations between ozone and fine particulate lags. The strongest correlations between lags of ozone was found for adjacent days (correlation coefficient of 0.74, 0.75). Correlations between lags of ozone two days apart dropped to 0.48 to 0.51. Fine particulate levels were more persistent over time, with correlations of 0.81-0.84 on adjacent lags and correlations did not drop to 0.5 or lower until lags that were 4 or more days apart. The correlation between ozone and fine particulates was weaker; the maximum correlation was 0.50.

Ozone levels were correlated with both day of week and month of the year, although these correlations were very small. Sundays were negatively correlated with ozone levels (correlation coefficient= -0.0556, p-value= 0.0251, Table 4-10). Ozone levels tended to rise during the work week with ozone being positively correlated with Fridays (correlation coefficient= 0.0482, p-value= 0.0521). Orange alerts were also positively correlated with Fridays (correlation coefficient= 0.0428, p-value= 0.0844).

Figure 4-11 shows the distribution of days at each ozone level, for days with and without ozone alerts and shows that the presence of alerts only overlaps in the middle of the distribution of ozone levels. No ozone alerts were issued on days with ozone levels less than 40 ppb and every day with ozone levels above 109 ppb had an ozone alert. The distribution on fine particulate levels overlapped more on days with and without ozone alerts (Figure 4-11). Ozone alerts were issued for virtually all levels of fine particulates. One alert was issued on days with 0-5μg/m^3 of fine particulates. No

ozone alerts were issued on the two days with the very highest fine particulate levels (55-59 $\mu g/m^3$).

Association between air pollution, ozone alerts and asthma exacerbations

Three different types of models were fit to estimate the association between air pollution, ozone alerts and asthma exacerbations. The objective of the first set of models was to examine the impact of previous day air pollution and ozone alerts in a simple, linear framework, shown in Table 4-11 (everyone) and Table 4-13 (by age group). Sensitivity analyses are shown in Table 4-12. The second set of models adds interactions between ozone, fine particulates and ozone alerts (Table 4-14), all measured on the previous day. The third set of models examines the role of lags -3 to lags +3 of ozone, fine particulates, and ozone alerts (Table 4-15, Table 4-16, Table 4-17) and does not include interactions between ozone, fine particulates, and ozone alerts. The full coefficient estimates are shown in the Appendix (page 115).

Previous day models without interactions, all subjects

Table 4-11 presents the percent change in outcomes associated with an increase in ozone and fine particulates, as well as the presence of an orange or red level ozone alert, including 95% confidence intervals. Model #1 does not include controls for ozone alerts. The hypothesis is that ignoring ozone alerts will bias the association between asthma exacerbations and ozone downward. Thus, I expect the association between asthma exacerbations and ozone should be lower in Model #1 than in Model #2, which controls for the presence of ozone alerts. This occurs for the high morbidity asthma outcomes, ER asthma visits and asthma hospitalizations, but not for the low morbidity outcomes and diabetes office visits. Controlling for ozone alerts not only increased the harmful (positive) association between ozone and asthma hospitalizations, but it also increased the statistical significance of ozone, which was not statistically significant in Model #1. An 20 ppb increase in ozone levels was associated with a 11.6% increase in asthma hospitalizations with a 95% confidence intervals of 2.5-20.6% in the model that controlled for ozone alerts (Model #2). In contrast, the same increase in ozone levels

was associated with a 7.0% increase in asthma hospitalizations (95% CI, -0.6%-14.6%), a downward bias of 40% due to ignoring ozone alerts.

The association between increases in ozone and asthma ER visits was weak, but did increase from -0.7 to 0.7% when ozone alerts were included as a control. Previous day ozone levels were actually negatively associated with the lower morbidity outcomes (office visits and drug fills) in Models 1 and 2, although none of these associations was statistically significant.

Previous day ozone alerts were protective (negatively associated with outcomes) for the high morbidity outcomes (asthma ER and hospitalizations) but not for the low morbidity outcomes. Orange Level ozone alerts were associated with 14.1% fewer asthma inpatient stays (95% CI, -27.9%, -0.3%) and 3.8% fewer asthma ER visits (95% CI, -14.5%, 6.8%) in the full model (Model 2 in Table 4-11). Red Level ozone alerts were associated with a larger protective impact than the orange level. Red alerts were associated with 19.9% fewer asthma hospitalizations (95% CI, -42.5%, 2.6%) and 10.5% fewer asthma ER visits (95% CI, -28.1%, 7.2%) in the full model (Model #2).

The direction of the associations estimated for the lower morbidity asthma outcomes (asthma office visits, OSC and SABA fills) were not generally in the expected direction for ozone and ozone alerts. A 20 ppb increase in previous day ozone levels was associated with fewer asthma office visits, OSC and SABA fills, although none of these associations was statistically significant at 95% confidence levels. Ozone alerts were associated with more low morbidity asthma outcomes, not a protective effect. Orange alerts were associated with 8.5% more SABA fills (95% CI, 2.6%, 14.4%) and red alerts were associated with 4.4% more SABA fills (95% CI: -5.3%, 14.1%) (Model #2). Previous day orange and red alerts were not associated with any change in OSC fills in the full model that controlled for fine particulates (Model #2).

Fine particulates were positively associated with statistically significantly more asthma exacerbations for all outcomes, except for asthma hospitalizations. This relationship was statistically significant for OSC and SABA fills, but not for the other asthma outcomes. An increase of 10 μg/m3 in previous day fine particulates was

associated with 6.2% more OSC fills (95% CI: 1.9%, 10.4%) and 4.9% more SABA fills (95% CI: 1.7%, 8.2%). Model #3 explored the impact of controlling for fine particulates on estimates of the impact of ozone. Differences between Model #2 and Model# 3 were not statistically significant for ozone and ozone alerts. Both orange and red ozone alerts were found to be protective and were statistically significant in the model that excluded controls for fine particulates (model #3), although differences in the point estimates were not materially different from the full model (Model #2).

None of the air pollution or alert measures were significantly associated with diabetes office visits. An increase in previous day ozone was associated with fewer diabetes office visits and an increase in fine particulates was associated with a small increase in diabetes office visits. Both measures of ozone alerts were associated with more diabetes office visits.

Day of week and month were important predictors of utilization of services for asthma and diabetes. Asthma ER visits were significantly more likely to occur on Sundays than any other day of the week (see coefficients shown in Appendix Table A-1). Asthma inpatient stays were more likely to occur during the week and not on Federal holidays. Asthma inpatient stays were most likely to occur on Monday, and were 135% more likely to occur on a Monday than on Sundays (significant at 95% confidence levels). Asthma inpatient stays were about 51% less likely to occur on Federal Holidays than on Sundays; this relationship was statistically significant at 95% confidence levels (coefficients are shown in Appendix Table A-2). Asthma outpatient visits were more common Monday-Saturday than Sundays and Federal Holidays. An asthma outpatient visit was 91% less likely to occur on a Federal Holiday than on a Sunday (Appendix Table A-3). A similar pattern was seen for diabetes office visits, with a little larger probability of having a visit during the normal workweek than for asthma office visits (Appendix Table A-6). Drug fills were also more likely during the work week than weekends and holidays. SABA fills were 283% more likely on a Monday than on a Sunday and were 67% less likely on Federal Holidays (Appendix Table A-5). Similar relationships for day of week were observed for SABA fills (Appendix Table A-4).

Consistent with other studies, utilization of asthma care peaked during September. In September, there were 3.6% more asthma ER visits, 18.7% more asthma inpatient stays and 10% more asthma outpatient visits, SABA fills, and OSC fills than in May. Diabetes office visits were more common June-September than in May and October with peak visits in July (13% more visits than in May).

An increase in temperature was associated with an improvement in outcomes. A 10 °F increase in previous day temperature was associated with 36% fewer asthma ER visits, 2% fewer asthma inpatient stays, 15% fewer asthma office visits, 12% fewer diabetes office visits, 13% fewer OSC fills, and 16% fewer SABA fills[3]. A one percentage point increase in humidity levels on the previous day was associated with a small decrease in outcomes (<1%), except for inpatient stays which was associated with a small (<1%) increase in stays. Precipitation was not significantly associated with asthma exacerbations. Days with hail or thunder were more likely to have SABA and OSC fills and diabetes office visits (significant at 95% confidence levels). Hail or thunder on the previous day was associated with a 5% increase in SABA fills. Hail or thunder was also positively associated with asthma ER visits and inpatient stays, although these associations were not statistically significant at 95% confidence levels.

The number of subjects eligible for the outcome was strongly related to the number of visits, fills or stays each year. A 100,000 increase in the number eligible was associated with a 62% (OSC) to 97% (Diabetes Office Visits) increase in the number of visits, fills or stays.

Sensitivity analyses of previous day models, all ages

I conducted a sensitivity analysis (Table 4-12) to assess the impact of alternative specifications and alternative data on the base models that related previous day ozone, fine particulates and ozone alerts with asthma outcomes. Models 1-5 exclude the first two and last two years of data. Model 2 uses apparent temperature, instead of the

[3] These estimates were generated by increasing temperature by 10 degrees or humidity by 1% point, recalculating the interaction variables (temperature^2, humidity^2, temperature* humidity, temperature^2*humidity^2), and predicting the number of visit, stays of fills. This number of visit, stays, or fills was then compared with the baseline level of visits or stays and the percent change was calculated.

polynomial of temperature and humidity. Models 3, 4, and 5 control for weather with temperature and humidity without the interaction and square terms. Models 4 and 5 exclude the indicators for each month. Model 5 uses the asthma-only sample, where asthma was defined by an asthma diagnosis in 2005. For inpatient stays, I also present model 0, which is the same as the base model except the distribution is poisson, not negative binomial. Results were very similar for the poisson and negative binomial models. Overall, the biggest impact on the results was changing the years of data (especially for ER visits) and changing the sample (especially for asthma inpatient stays).

For asthma ER visits and inpatient stays, limiting the data to only 2002-2006 increased the size of the associations with ozone and ozone alert (model 1): ozone became more harmful (more positive) and ozone alerts became more strongly protective (more negative) compared with the base model. Limiting the data to 2002-2006 increased the harmful association between ozone and inpatient stays by 57%, from 10.5% in Model 0 to 16.5% in Model 1. In the 2000-2008 data, fine particulates were associated with more asthma ER visits or inpatient stays but were associated with fewer visits or stays when the first two and last two years of data were excluded, although none of these relationships were statistically significant. For asthma office visits, OSC fills, and SABA fills, an increase in previous day ozone levels was associated with fewer visits or fills in the base model but was associated with more visits or fills when the data were limited to 2002-2006. An increase in fine particulates was associated with an increase in asthma office visits, OSC and SABA fills in both the base model and model that was limited to 2002-2006 data, although the strength of this association was lower in the 2002-2006 data (Model 1). Ozone alerts were associated with more asthma office visits, SABA and OSC fills in both the base model and models limited to 2002-2006 data.

Controlling for weather using apparent temperature (Model 2 in Table 4-12) and no interactions or squares (Model 3) yielded similar results as the models that controlled for weather with a polynomial of temperature and humidity (Model 1). In the model with apparent temperature, a 20 ppb increase in previous day ozone was

associated with 12.1% more asthma inpatient stays (Model 1) while the model that included the polynomial of temperature and relative humidity(base model) found a 36% larger association (ozone was associated with a 16.5% increase in hospital stays).

Excluding the controls for month (Model 4) did not alter conclusions in a substantive way, although in some cases altered the magnitude of the associations. In Model 4, an ozone alert was associated with 13.7% fewer asthma ER visits, which is a 41% larger association than observed in Model 3 that did include controls for month.

The final sensitivity analysis assessed whether selecting only subjects with asthma would yield different findings than the base model where the sample at-risk for asthma was everyone enrolled in a plan, not just asthmatics. The largest difference was observed for asthma inpatient stays. An increase in ozone was associated with more inpatient stays in the general sample (Model 4) but with fewer inpatient stays in the asthma-only sample (Model 5). The direction of the association with inpatient stays also switched for fine particulates. Ozone alerts were strongly associated with fewer inpatient stays and were statistically significant in all models using the entire sample but had a much smaller association in the asthma-only sample and was not statistically significant (Model 5). Coefficients and standard errors for the models in the sensitivity analysis are shown in the Appendix Table A-15 to Table A-18.

Previous day models without interactions, children and adults

Table 4-13 presents results using the same specification as Model #2 in the previous analysis (includes ozone, fine particulates and alerts) for children age 5-19 and adults age 20-54. The negative binomial model could not estimate the alpha parameter for asthma ER visits and hospitalizations for adults, so these results are shown with the simpler poisson model. By age group, results were qualitative similar to the models of everyone, age 0-64. Results for ozone and ozone alerts were generally in the hypothesized direction for high morbidity outcomes but not for the lower morbidity outcomes.

For children, the only statistically significant associations were for SABA fills (rescue inhalers). Orange alerts on the previous day were associated 10.8% more SABA

fills (95% CI: 3.5%, 18.2%). Some associations were close to being statistically significant at 95% confidence levels. An 20 ppb increase in previous day ozone was associated with 8.9% more asthma ER visits by children (95% CI: -0.7%, 18.5%). An increase in previous day ozone was associated with fewer SABA fills (-3.2%, 95% CI: -6.6%, 0.2%) and diabetes office visits (-9.6%, 95% CI: -19.0%, -0.2%). A 10 μg/m3 increase in fine particulates was generally associated with fewer acute asthma visits (ER and inpatient) and more of the less acute outcomes, although these associations were not statistically significant at 95% confidence levels.

Significant associations were found for asthma hospitalizations, SABA fills, and diabetes office visits for adults. A 20 ppb increase in previous day ozone was associated with a 12.5% increase in asthma hospitalizations by adults (95% CI: 0.4%, 24.6%) but a 3.3% decrease in SABA fills (95% CI: -6.3%, -0.4%) and 4.8% fewer office visits for diabetes (95% CI: -8.9%, -0.7%). An orange alert was associated with 15.5% fewer asthma hospitalizations (95% CI: -33.6%, 2.7%) and 9.3% more SABA fills by adults (95% CI: 2.9%, 15.7%). A red or purple alert was associated with 22.1% fewer asthma hospitalizations by adults (95% CI: -51.4%, 7.2%). A 10 $\mu g/m^3$ increase in fine particulates was associated with a 5.6% increase in SABA fills by adults (95% CI: 2.1%, 9.1%).

The association between visits, fills, and stays with days of the week was similar for children and adults. Seasonality, especially the September peak, was more pronounced in children than adults. Coefficients and standard errors for the models in Table 4-13 are shown in Appendix Table A-7, Table A-8 and Table A-9.

Interactions between ozone, fine particulates, and ozone alerts

Table 4-14 presents results from the models that allow for interactions between ozone, fine particulates, and ozone alerts. Since the model is non-linear in ozone, fine particulates, and ozone alerts, the associations vary depending on where in the distribution the effect is estimated. Thus I present results in the table at very specific points in the distribution: for an increase in ozone from 70 to 90 ppb and an increase in fine particulates from 15 to 25 $\mu g/m^3$ on days with and without ozone alerts (orange or

higher). These nonlinear relationships are easier to understand graphically as a dose response relationship, where the dose is ozone and the response is visits, fills or stays (shown in Figure 4-12 for ozone and Figure 4-13 for fine particulates).

The relationship between ozone and outcomes was negative on days *with* and ozone alert for each of the outcomes except for OSC fills. On days *without* an ozone alert, worse ozone levels were associated with more of the acute outcomes (ER and hospital) but fewer of the drug and outpatient outcomes. The lines for days with and without an ozone alert in Figure 4-12 crossed, indicating that at low levels, alerts were not protective but may have been protective at higher levels of ozone. For both asthma and diabetes outpatient visits, increases in ozone levels was associated with fewer visits on days with and without ozone alerts, although none of these relationships were statistically significant.

The dose-response graphs of fine particulates (Figure 4-13) are strikingly different than those for ozone (Figure 4-12). On days with an ozone alert, an increase in fine particulates was associated with more visits, fills or stays, except for asthma inpatient stays and diabetes office visits where the relationship was flat to slightly negative. Days with ozone alerts typically had more visits, stays of fills and the lines crossed only for two for the outcomes (OSC fills and asthma office visits). The relationship between fine particulates and visits, fills, and stays was relatively flat on days *without* an ozone alert.

Similar to the models without the air pollution-alert interactions, significant results were found for asthma hospital stays (Table 4-14). An increase in ozone levels from 70 to 90 ppb on days *without* an ozone alert was associated with a 12.35% increase in asthma hospital stays (95% CI: 1.96%, 23.75%, very similar to the association observed in the model without interactions (Table 4-11). The same increase in ozone levels was associated with a 27.92% decrease in stays on days *with* an ozone alert (95% CI: -69.03, 51.51%). For inpatient stays (upper right graph of Figure 4-12), we see that on days without an ozone alert, an increase in ozone levels was associated with an increase in asthma inpatient stays. Specifically, a 20 ppb increase in ozone levels was

associated with 12.35% more asthma inpatient stays. However the slope of the line for days with an ozone alert was negative, meaning that higher ozone levels were associated with fewer inpatient stays, although this decrease was not statistically significant. The difference between the two lines in Figure 4-12 is the protective impact of ozone alerts. At 90 ppb, an orange or higher ozone alert was associated with 32% fewer asthma inpatient stays, which is about twice the protective association as seen in the model without interactions. In the model without air pollution-alert interactions, orange level ozone alerts were associated with 14% fewer asthma hospitalizations and red or higher alerts were associated with 20% fewer asthma hospitalizations.

For fine particulates, both lines in the dose-response graph were relatively flat, indicating that an increase in fine particulates was not associated with an increase in asthma hospital stays (top graph in right column of Figure 4-13). The line for ozone alerts is above the line for days without an ozone alert, indicating that days without an ozone alert had 28.04% fewer asthma hospitalizations, holding all other variables constant and with fine particulates set to 25$\mu g/m^3$.

For both SABA fills and OSC fills, a significant relationship was observed for an increase in fine particulates on days without an ozone alert. On days without an ozone alert, an increase from 15 to 25 $\mu g/m^3$ fine particulates was associated with a 6.05% increase in OSC fills (95% CI: 0.77%, 11.34%) and a 6.69% increase in SABA fills (95% CI: 2.77%, 10.59%). The other relationship that was statistically significant was for orange alerts and SABA fills. An orange level ozone alert on the previous day was associated with 15.84% more SABA fills (95% CI: 5.975, 26.61%), although red or higher level ozone alerts on the previous day were associated with 9.33% fewer SABA fills (95% CI: -35.82%, 47.66%).

Models with lags -3 through lag +3

Significant relationships for lags of ozone and ozone alerts were found for asthma inpatient stays, but not for asthma ER visits, similar to previous results. In the lag -3 through lag+3 model (Table 4-15), a 20 ppb increase in ozone on the previous day

(lag -1) was associated with 19.6% more asthma inpatient stays (95% CI: 6.2%, 32.9%), a 69% larger association than found in the previous day model that did not include other lags (Table 4-11). However, lag -2 of ozone was associated with 13% fewer asthma inpatient stays (95% CI: -21.8%, -4.2%). Lag +3 of ozone was also associated with fewer inpatient stays at 95% confidence levels. The previous day lag (lag -1) of orange alerts was associated with 16.2% fewer asthma inpatient stays (95% CI: -30.9%, -1.5%), a 15% larger association than found in the model with only the previous day lag (Table 4-11). The association with red or higher ozone alerts on the previous day (lag -1) was also higher in the lag -3 to lag +3 model. Red or higher alerts on the previous day were associated with 27.6% fewer asthma inpatient stays (95% CI: -52.3%, -2.8%), a 40% larger association than observed in the model without the additional lags (19.9% fewer stays, Table 4-11).

Highly variable results by lags (i.e. signs flipping from one lag to another) may indicate instability in results due to strong day-to-day correlations. This is observed for ozone for inpatient stays where the signs switch on each lag. One solution is to examine all of the lags in sum, which may indicate the net impact. The sum of all of the lags is 5.5%, meaning that on net, ozone is positively associated with asthma inpatient stays. The sum of the lags 0 to lag -3 is 10.6%, indicating that the past lags were more strongly associated with increases in asthma inpatient stays than future lags. The sum of the lags of fine particulates added up to -4.0% meaning that fine particulates were associated with fewer asthma inpatient stays. Lags 0 to -3 were associated with 2.3% fewer asthma inpatient stays. The sum of the orange alert lags indicated that orange level ozone alerts were associated with 4.9% fewer asthma inpatient stays over lag -3 to lag +3. The protective impact of ozone alerts was stronger when only the past and present lags (lag 0 to lag -3) are included; orange alerts were associated with 21.2% fewer asthma inpatient stays. The sum of past and present lags of red or purple alerts was -16.4%, indicating that past lags of red or higher alerts was associated with fewer inpatient stays, a protective relationship. Future lags of red or higher alerts were associated with more asthma inpatient stays (lags +1 to lag +3 add up to 28.2% more stays).

For Asthma ER visits, lag-1 was associated with more visits but not the other past lags so on net, past and present lags of ozone were associated with 4.4% fewer asthma ER visits (not the hypothesized direction). Ozone alerts were associated with more asthma ER visits for all lags except for lag -1. Red or higher ozone alerts were associated with fewer asthma ER visits for lags -3 and lag -1, but not other lags. Over lags -3 to lag 0, red or higher ozone alerts were associated with 1.4% more ER visits. The sum of lags -3 to lag -1 indicated that red or higher alerts were associated with 11.5% fewer asthma ER visits.

Past lags of ozone were associated with fewer asthma office visits. Same day and future lags of ozone were associated with more asthma office visits, except for lag +1. An increase in fine particulate levels was associated with 12.3% more asthma office 3 days later (95% CI: 3.7%, 20.9%). Past and same day lags of fine particulate was associated with 4.1% more asthma office visits (sum of lags -3 to lag 0) and the sum of future increases in fine particulates were associated with 3.8% more asthma office visits. Future lags of red or higher ozone alerts were significantly associated with asthma office visits, but in different directions. Two days before a red or purple ozone alerts experienced 20.5% more asthma office visits (95% CI: 1.5%, 39.5%) but 14.4% fewer visits (95% CI: -27.0%, -1.8%) 3 days before a red or purple alert. On net, future (lag +1 to lag +3) red or higher alerts were associated with 0.7% more asthma office visits and lags 0 to lag -3 of red or higher alerts were associated with 8.4% more visits, indicating that past alerts were more important than future expectations for asthma office visits.

Some of the lags of ozone and fine particulates were associated with diabetes office visits at statistically significant levels. An increase in the next day's ozone level (lag +1) was associated with 7.1% fewer diabetes office visits (95% CI: -12.5%, -1.8%). On net (lags -3 to lag +3), an increase in ozone was associated with 5.7% fewer diabetes office visits. An increase in fine particulate three days earlier was associated with 11.3% more diabetes office visits (95% CI: 1.7%, 21.0%).

Similar to models without the additional lags, an increase in ozone levels on the previous day was associated with fewer SABA fills (-3.8%, 95% CI: -7.5%, -0.2%). Lags -3 to lag 0 values of ozone was cumulatively associated with no change in SABA fills (-0.2%). Future lags of ozone (lags +1 to +3) were cumulatively associated with 3.1% fewer SABA fills. All lags of orange ozone alerts were associated with more SABA fills. Cumulatively, lags -3 to 0 of orange alerts were associated with 11.6% more SABA fills. Lag -1 was statistically significant (7.1% more fills, 95% CI: 0.7%, 13.5%). Future lags of orange level ozone alerts were associated with 7.9% more SABA fills. Red or higher ozone alerts two days in the future were associated with 12.3% more SABA fills today (95% CI: 0.2%, 24.5%). Cumulatively, lags -3 to 0 of red or higher alerts was associated with 0.1% fewer SABA fills and future lags (lag +1 to lag +3) were associated with 8% more SABA fills. None of the lags of ozone, fine particulates or ozone alerts were related to OSC fills at statistically significant levels.

Results Tables

Table 4-1. Subjects' residence, gender, age, and type of health plan, by year

	2000	2001	2002	2003	2004	2005	2006	2007	2008
Number of enrollees	**24,615**	**31,962**	**59,713**	**137,491**	**170,453**	**219,685**	**403,536**	**427,891**	**201,667**
Gender									
Female	47.6	49.6	51.4	50.5	51.0	50.6	52.0	52.3	51.5
Male	52.4	50.4	48.6	49.5	49.0	49.4	48.0	47.7	48.5
Current Age									
0-17 years	30.9	28.6	28.8	28.2	27.9	27.8	27.4	27.0	28.4
18-34 years	19.1	21.6	22.1	21.9	21.8	21.3	21.5	21.6	22.0
35-44 years	21.5	19.0	18.6	18.8	18.0	17.5	17.5	17.2	16.5
45-54 years	17.3	17.6	17.7	18.5	19.1	19.7	19.9	19.9	19.6
55-64 years	11.2	13.2	12.8	12.6	13.3	13.8	13.6	14.2	13.6
Type of Health Plan									
Comprehensive	3.9	11.9	6.9	3.7	11.2	8.4	3.8	0.5	0.9
Exclusive Provider Organization (EPO)	0.0	0.0	6.5	1.0	0.1	0.5	0.2	0.2	0.7
Health Maintenance Organization (HMO)	2.6	3.0	5.4	27.1	19.8	29.2	17.6	16.5	27.0
Point of Service Plan (POS)	20.0	17.9	9.0	13.5	11.3	9.0	8.5	11.3	13.8
Preferred Provider Organization (PPO)	15.8	20.3	53.7	50.2	48.4	46.0	63.0	61.9	44.8
Capitated Point of Service Plan	57.6	44.8	14.1	1.4	0.6	0.0	0.0	0.0	0.0
Consumer Driven Health Plan (CDHP)	0.0	0.0	0.0	0.1	6.5	6.2	5.5	4.1	5.5
Not classified	0.0	2.1	4.4	3.1	2.2	0.6	1.4	5.4	7.3
Wage classification									

	2000	2001	2002	2003	2004	2005	2006	2007	2008
Salaried	41.1	36.8	24.3	12.9	14.0	22.9	13.5	13.5	31.4
Hourly	37.3	44.8	35.3	17.5	20.4	24.1	12.8	13.1	35.9
Not classified	21.6	18.4	40.3	69.6	65.6	53.0	73.6	73.4	32.7
Union status									
Union negotiated plan	17.7	25.4	14.3	7.1	12.3	14.9	7.5	7.5	16.0
Not union	82.3	74.6	85.7	92.9	87.7	85.1	92.5	92.5	84.0
Type of beneficiary									
Employee	40.2	41.4	43.9	45.1	45.0	44.3	47.6	48.1	44.0
Dependent	59.8	58.6	56.1	54.9	55.0	55.7	52.4	51.9	56.0

Table 4-2. Number of subjects and asthma prevalence rates, by year

Year		Dallas-Fort Worth, any enrollment	Dallas-Fort Worth, enrolled entire ozone season			
			All enrollees		Asthma, current	
			Medical Plan	Medical & Drug Plan	Medical Plan	Medical & Drug Plan
2000	N	30,259	24,615	23,536	871	795
	per 100		81.3%	95.6%	3.5%	91.3%
2001	N	45,010	31,962	31,355	1,163	1,028
	per 100		71.0%	98.1%	3.6%	88.4%
2002	N	78,405	59,713	50,976	2,010	1,629
	per 100		76.2%	85.4%	3.4%	81.0%
2003	N	181,394	137,491	115,904	4,642	3,789
	per 100		75.8%	84.3%	3.4%	81.6%
2004	N	220,404	170,453	152,728	8,277	5,219
	per 100		77.3%	89.6%	4.9%	63.1%
2005	N	280,627	219,685	200,465	8,277	7,114
	per 100		78.3%	91.3%	3.8%	85.9%
2006	N	538,627	403,536	267,455	15,992	9,008
	per 100		74.9%	66.3%	4.0%	56.3%
2007	N	570,581	427,891	329,823	18,278	12,731
	per 100		75.0%	77.1%	4.3%	69.7%
2008	N	241,870	201,682	196,798	6,130	5,596
	per 100		83.4%	97.6%	3.0%	91.3%
2002-2006	N (enrollee-years)	1,299,457	990,878	787,528	39,198	26,759
	mean		76.25%	79.48%	4.0%	68.3%
2000-2008	N (enrollee-years)	2,187,177	1,677,028	1,369,040	65,640	46,909
	mean		76.68%	81.63%	3.91%	71.46%

Asthma current is the number of patients who were treated for asthma in that year (prevalence of asthma treatment). All subjects in the study were required to be enrolled in a medical plan. Only subjects enrolled in drug plans were included in the analyses of drug outcomes.

Table 4-3. Asthma prevalence for adults and children

Year	Children age 5-19			Adults age 20-54		
	Number of subjects	Number treated for asthma	Prevalence rate, per 100 subjects	Number of Subjects	Number treated for asthma	Prevalence rate, per 100 subjects
2000	6,753	342	5.1	13,465	343	2.5
2001	8,084	397	4.9	17,513	440	2.5
2002	14,954	697	4.7	32,943	753	2.3
2003	34,366	1,577	4.6	77,011	1,756	2.3
2004	42,136	2,142	5.1	94,710	2,278	2.4
2005	54,315	2,850	5.2	121,082	3,058	2.5
2006	97,912	5,222	5.3	224,524	6,037	2.7
2007	102,520	5,985	5.8	236,932	7,268	3.1
2008	50,281	2,130	4.2	110,179	2,382	2.2
TOTAL	411,321	21,342	5.2	928,359	24,315	2.6

Prevalence rate is based on number treated for asthma (from diagnosis codes) each year. Table includes subjects enrolled in a medical plan. Results were similar for subjects also enrolled in drug plan. 82.0% of children and 81.9% of adults were also enrolled in a drug plan and the prevalence rate of asthma was the same in the drug plan group as the entire sample.

Table 4-4. Rate of visits, inpatient stays, and drug fills, by year

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2002-2006	2000-2008
Emergency Room visits for asthma											
Rate per 1,000 enrollees	2.03	3.25	2.75	2.43	2.81	3.00	2.59	3.17	2.39	2.71	2.79
Rate per 100 with asthma	5.74	8.94	8.16	7.20	5.79	7.97	6.55	7.42	7.88	6.85	7.13
Inpatient stays for asthma											
Rate per 1,000 enrollees	0.69	0.56	0.84	1.43	1.31	1.12	1.56	1.63	0.76	1.36	1.33
Rate per 100 with asthma	1.95	1.55	2.49	4.24	2.71	2.98	3.93	3.82	2.50	3.43	3.40
Doctor office visits for asthma											
Rate per 1,000 enrollees	25.35	23.65	20.41	21.03	21.42	22.61	24.03	26.59	19.02	22.63	23.27
Rate per 100 with asthma	71.64	65.00	60.65	62.30	44.11	60.00	60.64	62.25	62.58	57.21	59.44
Oral Systemic Corticosteroid Fills with a confirmatory asthma diagnosis											
Rate per 1,000 enrollees	11.13	11.13	11.67	11.12	11.24	12.23	11.00	11.62	9.62	11.42	11.20
Rate per 100 with asthma	32.96	33.95	36.53	34.02	32.90	34.47	32.65	30.09	33.85	33.61	32.68
Short-acting Beta-Agonists (SABA) fills (rescue inhaler)											

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2002-2006	2000-2008
Rate per 1,000 enrollees	72.40	77.08	74.27	70.49	69.10	71.00	62.76	58.51	53.03	67.97	63.83
Rate per 100 with asthma	214.34	235.12	232.41	215.62	202.22	200.08	186.33	151.59	186.49	200.04	186.29
Inhaled Corticosteroids Fills (long-term controller)											
Rate per 1,000 enrollees	109.28	118.71	123.65	125.91	120.96	126.60	113.71	98.92	96.61	120.84	111.83
Rate per 100 with asthma	323.52	362.06	386.92	385.17	353.98	356.75	337.60	256.26	339.76	355.62	326.36
Long-Acting Beta-Agonists (LABA) fills (long-term controller)											
Rate per 1,000 enrollees	12.53	22.10	32.86	32.82	34.62	38.38	32.15	27.33	26.76	34.36	30.92
Rate per 100 with asthma	37.11	67.41	102.82	100.40	101.30	108.14	95.47	70.81	94.12	101.12	90.24

Notes: For the rate per 100 with asthma, asthma was defined as any treatment for asthma during the calendar year. Includes all visits, stays, and fills during the calendar year (was not limited to the ozone season May – October). A full year of data was not available for 2008 (only January-September).

Table 4-5. Rate of visits, inpatient stays, and drug fills by age group

	Children age 5-19	Adults age 20-54
Inpatient stays for asthma		
Rate per 1,000 subjects	0.92	1.33
Rate per 100 with asthma	1.78	5.08
ER visits for asthma		
Rate per 1,000 subjects	4.63	2.02
Rate per 100 with asthma	8.93	7.70
Office visits for asthma		
Rate per 1,000 subjects	29.79	14.88
Rate per 100 with asthma	57.41	56.81
Office visits for diabetes		
Rate per 1,000 subjects	4.72	43.86
Rate per 100 with asthma	9.09	167.46
Fills of oral systemic corticosteroids (OSC)		
Rate per 1,000 subjects	12.89	8.42
Rate per 100 with asthma	25.03	33.53
Fills of short-acting beta-agonists (quick relief inhaler)		
Rate per 1,000 subjects	77.77	48.91
Rate per 100 with asthma	151.00	194.84

Rate per 100 with asthma is based on the number of subjects treated for asthma during the year (have any asthma diagnoses).

Table 4-6. Utilization rates for the general sample and 2005 asthma cohort

	Main Analysis 2000-2008		2005 Asthma cohort 2002-2006		
	Rate per 100 asthma	Rate per 1,000 general population	Rate per 100 asthma	Rate per 1,000 general pop (prev=3.8 per 100)	Rate per 1,000 general pop (prev=4.0 per 100)
ER visits for asthma	7.13	2.79	12.19	3.21	3.05
Inpatient stays for asthma	3.40	1.33	3.48	0.92	0.87
Office visits for asthma	59.44	23.27	78.14	20.56	19.54
OSC fills	32.68	11.20	48.55	12.78	12.14

Rate per 100 with asthma in the main analysis is calculated based on people who had an asthma diagnosis during 1 calendar year. Rate per 100 with asthma in the 2005 asthma cohort is based on people with asthma in 2005 and then their visits are followed over time.

Table 4-7. Use of controllers by general sample and 2005 asthma cohort

	No Asthma diagnosis			
	No controller	**Controller**	**TOTAL**	**% use controller**
	No asthma diagnoses			
2000	19,931	1,825	21,756	8.4%
2001	26,136	2,477	28,613	8.7%
2002	42,804	3,991	46,795	8.5%
2003	98,111	9,687	107,798	9.0%
2004	127,799	13,121	140,920	9.3%
2005	167,263	17,756	185,019	9.6%
2006	225,727	22,391	248,118	9.0%
2007	281,357	25,817	307,174	8.4%
2008	167,637	15,780	183,417	8.6%
TOTAL	1,156,765	112,845	1,269,610	8.9%
	Asthma diagnosis, but not in the 2005 cohort			
2000	957	560	1,517	36.9%
2001	1,457	799	2,256	35.4%
2002	2,056	1,256	3,312	37.9%
2003	3,525	2,609	6,134	42.5%
2004	4,608	3,169	7,777	40.7%
2005	5,580	2,752	8,332	33.0%
2006	8,245	6,138	14,383	42.7%
2007	11,457	7,313	18,770	39.0%
2008	5,934	4,240	10,174	41.7%
TOTAL	43,819	28,836	72,655	39.7%
	2005 Asthma cohort			
2000	166	97	263	36.9%
2001	278	208	486	42.8%
2002	473	396	869	45.6%
2003	1,051	921	1,972	46.7%
2004	2,061	1,970	4,031	48.9%
2005	2,660	4,454	7,114	62.6%
2006	2,265	2,689	4,954	54.3%
2007	1,850	2,029	3,879	52.3%
2008	1,775	1,432	3,207	44.7%
TOTAL 2000-2008	12,579	14,196	26,775	53.0%
TOTAL 2002-2006	8,510	10,430	18,940	55.1%

Annual counts are number of patients, total counts are number of patient-years.

Table 4-8. Accuracy of ozone alerts

	2000	2001	2002	2003	2004	2005	2006	2007	2008
Orange or higher Alert, days	58	53	56	54	38	59	36	19	31
Red Alert or higher, days	19	4	16	14	12	14	4	4	1
Purple Alert, days	0	0	0	1	0	0	0	0	0
Exceeded target level, days	36	28	37	31	25	44	31	12	30
Accurate alerts, days	31	26	33	26	19	33	28	9	15
Missed Alerts, days	5	2	4	5	6	11	3	3	15
False alarms, days	22	25	19	23	13	15	5	7	1
Accurate no forecast, days	121	129	124	125	140	114	145	162	138
Target days correctly predicted, percent of target days	86%	93%	89%	84%	76%	75%	90%	75%	50%
Correct alerts, percent of alert days	53%	49%	59%	48%	50%	56%	78%	47%	48%
Days in season with correct forecasts, percent	83%	84%	85%	82%	86%	80%	94%	93%	83%

Level Orange indicates Unhealthy for Sensitive Groups. Level Red indicates Unhealthy, and Level Purple indicates Very Unhealthy.
Target value 2000-2007 was 85 ppb or higher 8-hour average for Orange or higher alerts. In 2008, the target was lowered to 76 ppb 8-hour ozone.

Table 4-9. Description of air quality and weather, showing mean, minimum, maximum, and interquartile range 2000-2008

	Mean	Min	Max	IQR	25 pctile	75 pctile	N
Ozone, 1-hr maximum, ppb	73	14	161	35	56	91	1625
Ozone, 8-hr maximum, ppb	64	11	131	29	49	78	1625
Fine particulates, $\mu g/m^3$	14.5	2.1	56.7	8.1	10.5	18.6	1621
Temperature, average daily °F	80.1	49.5	95.9	10.5	74.9	85.4	1617
Relative humidity, %	73%	0%	97%	14%	66%	80%	1617
Precipitation, inches	0.31	0.00	5.67	0.29	0.16	0.45	1617
Apparent temperature, daily average, °F	85.6	44.7	103.2	14.1	78.5	92.7	1617
Wind speed, knots	8.5	2.4	23.9	4.3	6.4	10.7	1617
Hail or thunder, indicator	38%	0%	100%				1625

IQR = interquartile range, the distance between the 25th and 75th percentiles (pctile)
Values calculated only for the ozone season, May – October of each year.

Table 4-10.Correlation between ozone, fine particulates and alerts with day of week, holidays, and month

	Ozone (8-hr), ppb	Orange Level Ozone Alert	Red or higher level ozone alert	Fine particulates, µg/m^3
Orange Level Ozone Alert	0.4957 (<0.001)	1		
Red or higher level ozone alert	0.4013 (<0.001)	-0.1183 (<0.001)	1	
Fine particulates, µg/m^3	0.5067 (<0.001)	0.2771 (<0.001)	0.3231 (<0.001)	1
Sunday	-0.0556 (0.0251)	-0.0157 (0.5273)	-0.0044 (0.8599)	-0.0306 (0.2177)
Monday	-0.0197 (0.4272)	-0.0298 (0.2300)	0.0262 (0.2904)	-0.0105 (0.6719)
Tuesday	-0.0094 (0.7056)	-0.0262 (0.2913)	-0.0052 (0.834)	0.0134 0.5892
Wednesday	0.003 (0.9036)	-0.0201 (0.4176)	-0.0122 (0.6244)	0.0089 0.7211
Thursday	0.0141 (0.5712)	0.0197 (0.4266)	-0.0122 (0.6244)	-0.008 0.747
Friday	0.0482 (0.0521)	0.0428 (0.0844)	0.0116 (0.6402)	0.0056 0.8226
Saturday	0.0196 (0.4302)	0.0295 (0.2344)	-0.004 (0.8730)	0.0213 0.3904
Federal Holiday	-0.0256 (0.3017)	0.0206 (0.4066)	-0.0098 (0.6921)	0.0187 0.4527
May	-0.0793 (0.0014)	-0.1511 (<0.001)	-0.1089 (<0.001)	-0.036 0.1473
June	0.0116 (0.6393)	0.0374 (0.1313)	-0.0045 (0.8549)	-0.0243 0.3278
July	0.0582 (0.0189)	0.116 (<0.001)	-0.0152 (0.5402)	0.024 0.3345
August	0.1807 (<0.001)	0.1078 (<0.001)	0.1939 (<0.001)	0.0612 0.0137
September	0.1004 (0.0001)	0.0707 (0.0043)	0.032 (0.1975)	0.1035 (<0.001)
October	-0.2835 (<0.001)	-0.1882 (<0.001)	-0.1015 (<0.001)	-0.133 (<0.001)

Correlation coefficient shown, p-values are parentheses.

Table 4-11. Previous day models without pollution-alert interactions: Percent change in outcomes associated with increases in air pollution and ozone alerts

	Model #1		Model #2		Model #3	
	Change visits	(95% CI for change in visits)	Change visits	(95% CI for change in visits)	Change visits	(95% CI for change in visits)
ER asthma visits						
Ozone	-0.7%	(-5.7%, 4.2%)	0.7%	(-5.0%, 6.5%)	1.6%	(-3.9%, 7.2%)
Fine PM	2.9%	(-3.1%, 8.9%)	3.6%	(-2.6%, 9.7%)		
Orange Ozone Alert			-3.8%	(-14.5%, 6.8%)	-2.8%	(-13.4%, 7.8%)
Red or higher Ozone Alert			-10.5%	(-28.1%, 7.2%)	-8.7%	(-26.5%, 9.0%)
Hospitalization for asthma						
Ozone	7.0%	(-0.6%, 14.6%)	**11.6%**	**(2.5%, 20.6%)**	**9.1%**	**(0.7%, 17.6%)**
Fine PM	-9.1%	(-16.9%, -1.3%)	-7.6%	(-15.7%, 0.4%)		
Orange Ozone Alert			**-14.1%**	**(-27.9%, -0.3%)**	**-15.6%**	**(-29.2%, -2.1%)**
Red or higher Ozone Alert			-19.9%	(-42.5%, 2.6%)	**-23.0%**	**(-44.5%, -1.5%)**
Office visits for asthma						
Ozone	-2.2%	(-5.7%, 1.4%)	-3.4%	(-7.4%, 0.6%)	-2.9%	(-6.8%, 1.0%)
Fine PM	2.1%	(-2.4%, 6.5%)	1.7%	(-2.8%, 6.2%)		
Orange Ozone Alert			5.1%	(-3.2%, 13.4%)	5.3%	(-3.1%, 13.6%)
Red or higher Ozone Alert			5.2%	(-8.8%, 19.2%)	5.9%	(-8.0%, 19.7%)
Emergency Medication: Oral Systemic Corticosteroid Fills						
Ozone	-1.6%	(-4.8%, 1.5%)	-1.7%	(-5.4%, 1.9%)	-0.2%	(-3.8%, 3.4%)
Fine PM	**6.2%**	**(2.0%, 10.4%)**	**6.2%**	**(1.9%, 10.4%)**		
Orange Ozone Alert			0.4%	(-6.9%, 7.6%)	1.4%	(-5.9%, 8.6%)
Red or higher Ozone Alert			0.5%	(-11.7%, 12.8%)	3.4%	(-9.0%, 15.9%)
Quick Relief Medication: Short-acting beta-agonists fills (no confirmatory asthma DX)						
Ozone	-1.6%	(-4.1%, 0.9%)	-3.3%	(-6.1%, -0.5%)	-2.1%	(-4.8%, 0.6%)

	Model #1			Model #2			Model #3		
	Change visits	(95% CI for change in visits)		Change visits	(95% CI for change in visits)		Change visits	(95% CI for change in visits)	
Fine PM	**5.3%**	**(2.1%,**	**8.5%)**	**4.9%**	**(1.7%,**	**8.2%)**			
Orange Ozone Alert				**8.5%**	**(2.6%,**	**14.4%)**	**9.3%**	**(3.4%,**	**15.3%)**
Red or higher Ozone Alert				4.4%	(-5.3%,	14.1%)	6.7%	(-3.1%,	16.5%)
Diabetes Office Visits									
Ozone	-2.8%	(-6.7%,	1.2%)	-4.2%	(-8.6%,	0.3%)	-4.0%	(-8.2%,	0.3%)
Fine PM	1.2%	(-3.9%,	6.2%)	0.7%	(-4.4%,	5.8%)			
Orange Ozone Alert				4.7%	(-4.6%,	14.0%)	4.7%	(-4.6%,	13.9%)
Red or higher Ozone Alert				8.4%	(-7.6%,	24.5%)	8.6%	(-7.3%,	24.5%)

The percent change in visits or fills was estimated for a 20 ppb increase in ozone levels and a 10 $\mu g/m^3$ increase in fine particulate levels . I hypothesize that increased ozone levels are harmful (expect a positive sign) and ozone alerts are protective (expect negative sign). Percent change in visits and 95% confidence intervals (in parentheses) were estimated using the delta method, implemented using the prvalue command in STATA. Associations that are different from zero at 95% confidence levels are shown in **bold**.

The regression was a negative binomial count model of visits, stays of fills. Ozone, fine particulates, ozone alert, and weather were measured on the previous day (lag-1). Weather was measured using a polynomial of temperature and humidity and the change in temperature and humidity from the previous day, plus precipitation, and an indicator for hail or thunder. The regression also included controls for day of week, month, federal holidays, and the number of subjects eligible for the outcome (enrolled in the medical plan for visits or stays and enrolled in a drug plan for fills). Coefficients and standard errors are shown in the Appendix (Table A-1 to Table A-6).

Table 4-12. Sensitivity analysis of previous day models without interactions, percent change in visits, fills and stays associated with increases in air pollution and ozone alerts

	Base Model	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Specification			Limit to 2002-2006	Same as 1, but use apparent temp instead of polynomial	Same as 1, but use temp and humidity without interactions	Same as 3, but exclude monthly indicators	Same as 4
Sample	General	General	General	General	General	General	Asthma only
Model (applies to all outcomes except for asthma inpatient stays)	Negative binomial	Negative binomial	Negative binomial	Negative binomial	Negative binomial	Negative binomial	Logit
Asthma ER visits							
Ozone, 20 ppb increase	0.7%		6.2%	4.1%	4.9%	3.6%	3.1%
Fine particulates, 10 µg/m^3 increase	3.6%		-2.0%	-2.2%	-2.1%	0.9%	**8.2%**
Orange ozone alert	-3.8%		-7.9%	-9.7%	-9.7%	-13.7%	-8.3%
Red or higher ozone alert	-10.5%		-12.2%	-11.9%	-12.3%	-14.2%	
Asthma Inpatient stays							
Model	Negative binomial	Poisson	Poisson	Poisson	Poisson	Poisson	Logit
Rate per 1,000 general	1.3%	1.4%					
Ozone, 20 ppb increase	11.6%	**10.5%**	**16.5%**	**12.1%**	**15.4%**	**12.9%**	-4.0%
Fine particulates, 10 µg/m^3 increase	-7.6%	-4.6%	-8.6%	-8.9%	-9.3%	-9.3%	10.6%
Orange ozone alert	**-14.1%**	**-15.8%**	**-24.9%**	**-26.9%**	**-26.8%**	**-25.4%**	-6.4%
Red or higher ozone alert	-19.9%	-21.4%	**-35.3%**	**-34.3%**	**-35.5%**	**-33.2%**	
Asthma Office Visits							
Ozone, 20 ppb increase	-3.4%		2.6%	3.6%	2.7%	1.9%	0.4%
Fine particulates, 10 µg/m^3 increase	1.7%		-2.5%	-2.8%	-2.6%	1.8%	**5.4%**

	Base Model	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Orange ozone alert	5.1%		4.0%	3.1%	3.2%	-1.6%	-3.4%
Red or higher ozone alert	5.2%		0.3%	-0.4%	0.1%	-0.5%	
Oral Systemic Corticosteroid (OSC) Fills							
Ozone, 20 ppb increase	-1.7%		3.2%	1.2%	2.1%	2.5%	**3.4%**
Fine particulates, 10 µg/m^3 increase	**6.2%**		2.4%	2.4%	2.4%	**6.6%**	**6.6%**
Orange ozone alert	0.4%		3.5%	2.1%	2.3%	-2.2%	-3.1%
Red or higher ozone alert	0.5%		1.9%	2.2%	1.8%	-3.7%	
Short-acting beta-agonists (SABA) fills							
Ozone, 20 ppb increase	-3.3%		1.1%	-0.2%	0.6%	0.0%	
Fine particulates, 10 µg/m^3 increase	**4.9%**		1.3%	2.0%	1.9%	**4.1%**	
Orange ozone alert	8.5%		**7.7%**	**7.4%**	**7.5%**	**5.9%**	
Red or higher ozone alert	4.4%		1.6%	2.1%	1.7%	1.8%	

Statistically significant associations (95% confidence levels) are shown in **bold**. Estimates of percent change and significance were generated using the delta method, implemented using STATA's prvalue command for the base model and models 1-4. Estimates from model #5 are based on the mfx command in STATA and then adjusted for a 20 or 10 point change in ozone or fine particulates. Results from the base model are shown in Table 4-11. Coefficients for base model are shown in Table A-10 to Table A-6. Coefficients for Models 0-4 are shown in Table A-15 to Table A-18.

Table 4-13. Previous day models by age group without pollution-alert interactions, percent change in outcomes associated with increases in air pollution and alerts

	Children age 5-19			Adults age 20-54		
	Change visits	(95% CI for change in visits)		Change visits	(95% CI for change in visits)	
ER asthma visits						
Ozone (20 ppb increase)	8.9%	(-0.7%,	18.5%)	-2.5%	(-10.6%,	5.5%)
Fine PM (10 μg/m^3 increase)	-6.8%	(-15.6%,	2.0%)	7.6%	(-2.0%,	17.1%)
Orange Ozone Alert	-6.1%	(-22.0%,	9.8%)	-3.2%	(-19.2%,	12.8%)
Red/purple Ozone Alert	-10.9%	(-37.7%,	15.9%)	8.4%	(-21.9% ,	38.8%)
Hospitalization for asthma						
Ozone (20 ppb increase)	5.5%	(-15.3%,	26.4%)	**12.5%**	**(0.4%,**	**24.6%)**
Fine PM (10 μg/m^3 increase)	-3.0%	(-24.1%,	18.1%)	-3.7%	(-15.2%,	7.9%)
Orange Ozone Alert	-11.1%	(-46.0%,	23.8%)	**-15.5%**	(-33.6%,	2.7%)
Red/purple Ozone Alert	-38.4%	(-87.5%,	10.6%)	-22.1%	(-51.4% ,	7.2%)
Office visits for asthma						
Ozone (20 ppb increase)	-2.0%	(-6.6%,	2.7%)	-2.9%	(-7.2%,	1.5%)
Fine PM (10 μg/m^3 increase)	3.5%	(-1.9%,	8.9%)	-0.4%	(-5.4%,	4.7%)
Orange Ozone Alert	3.7%	(-5.7%,	13.1%)	4.8%	(-4.3%,	13.9%)
Red/purple Ozone Alert	4.9%	(-10.9%,	20.6%)	3.7%	(-11.5%,	18.8%)
Emergency Medication: Oral Systemic Corticosteroid Fills						
Ozone (20 ppb increase)	-2.7%	(-8.9%,	3.5%)	1.2%	(-3.7%,	6.1%)
Fine PM (10 μg/m^3 increase)	5.0%	(-2.2%,	12.3%)	4.5%	(-0.9%,	10.0%)
Orange Ozone Alert	1.7%	(-11.0%,	14.4%)	-2.8%	(-11.9%,	6.3%)
Red/purple Ozone Alert	-2.9%	(-23.8%,	17.9%)	3.3%	(-12.5%,	19.1%)
Quick Relief Medication: Short-acting beta-agonists fills (no confirmatory asthma DX)						
Ozone (20 ppb increase)	-3.2%	(-6.6%,	0.2%)	**-3.3%**	**(-6.3%,**	**-0.4%)**
Fine PM (10 μg/m^3 increase)	2.3%	(-1.7%,	6.2%)	**5.6%**	**(2.1%,**	**9.1%)**
Orange Ozone Alert	**10.8%**	**(3.5%,**	**18.2%)**	**9.3%**	**(2.9%,**	**15.7%)**
Red/purple Ozone Alert	5.6%	(-6.3%,	17.6%)	51.2%	(16.1%,	86.3%)
Office Visits for diabetes						
Ozone (20 ppb increase)	-9.6%	(-19.0%,	-0.2%)	**-4.8%**	**(-8.9%,**	**-0.7%)**
Fine PM (10 μg/m^3 increase)	2.8%	(-9.3%,	14.8%)	3.6%	(-1.5%,	8.7%)
Orange Ozone Alert	12.7%	(-10.3%,	35.8%)	2.7%	(-5.9%,	11.4%)
Red/purple Ozone Alert	17.9%	(-23.0%,	58.7%)	10.3%	(-5.0%,	25.7%)

Estimates and 95% confidence intervals for the change in outcomes for an increase in ozone, fine particulates or ozone alert level were generated using the delta method, implemented with the prvalue command in STATA. I hypothesize that ozone is harmful (expect positive sign) and ozone alerts are protective (negative sign). ER visits and inpatient stays for adults were modeled with a poisson count model. All other outcomes were modeled using the negative binomial count model. The models included the same variables as in the previous table. Associations statistically different than zero at 95%confidence levels are in **bold**. Coefficients and standard errors from the models used to generate these estimates are shown in the Appendix (Table A-7 to Table A-9).

Table 4-14. Previous day models with pollution-alert interactions: percent change in outcomes associated with increases in air pollution and ozone alerts

	Estimate, %	95% Confidence interval, %	
Asthma ER visits			
Increase ozone from 70 to 90 ppb			
Days WITHOUT an ozone alert	3.84	(-3.19,	11.27)
Days WITH an ozone alert	-19.81	(-52.20,	24.91)
Increase $PM_{2.5}$ from 15 to 25 μg/m^3			
Days WITHOUT an ozone alert	3.58	(-4.33,	11.6)
Days WITH an ozone alert	46.94	(-50.91,	268.51)
Any ozone alert, orange level or higher	22.8	(-417.75,	204.95)
Any alert, set ozone = 90 ppb	-7.56	(-41.07,	42.7)
Any alert, set $PM_{2.5}$ = 25 μg/m^3	96.87	(-0.33,	325.72)
Orange Level ozone alert	-13.72	(-28.94,	5.52)
Red Level ozone alert	44.7	(-33.77,	489.17)
Asthma Hospital Stays			
Increase ozone from 70 to 90 ppb			
Days WITHOUT an ozone alert	**12.35**	**(1.96,**	**23.75)**
Days WITH an ozone alert	-27.62	(-69.05,	51.51)
Increase $PM_{2.5}$ from 15 to 25 μg/m^3			
Days WITHOUT an ozone alert	0.42	(-11.24,	13.42)
Days WITH an ozone alert	-1.97	(-85.87,	437.41)
Any ozone alert, orange level or higher	24.74	(-67.37,	1078.46)
Any alert, set ozone = 90 ppb	-32.42	(-65.34,	32.09)
Any alert, set $PM_{2.5}$ = 25 μg/m^3	28.04	(-60.81,	442.88)
Orange Level ozone alert	-16.96	(-40.22,	13.52)
Red Level ozone alert	54.52	(-62.86,	1524.98)
Asthma Outpatient Visits			
Increase ozone from 70 to 90 ppb			
Days WITHOUT an ozone alert	-2.97	(-7.79,	1.79)
Days WITH an ozone alert	-5.86	(-34.57,	33.85)
Increase $PM_{2.5}$ from 15 to 25 μg/m^3			
Days WITHOUT an ozone alert	5.42	(-0.51,	11.22)
Days WITH an ozone alert	33.68	(-27.56,	134.97)
Any ozone alert, orange level or higher	-2.89	(-46.8,	98.9)
Any alert, set ozone = 90 ppb	-2.62	(-26.37,	30.28)
Any alert, set $PM_{2.5}$ = 25 μg/m^3	30.8	(-17.03,	114.45)
Orange Level ozone alert	8.45	(-5.63,	25.33)
Red Level ozone alert	-10.2	(-48.73,	79.42)
Fills of Oral Systemic Corticosteroids (OSC)			
Increase ozone from 70 to 90 ppb			
Days WITHOUT an ozone alert	-0.85	(-5.36,	3.66)
Days WITH an ozone alert	5.04	(-26.46,	36.55)
Increase $PM_{2.5}$ from 15 to 25 μg/m^3			

	Estimate, %	95% Confidence interval, %
Days WITHOUT an ozone alert	**6.05**	**(0.77, 11.34)**
Days WITH an ozone alert	75.81	(-18.43, 170.06)
Any ozone alert, orange level or higher	-27.11	(-71.24, 17.03)
Any alert, set ozone = 90 ppb	-14.51	(-36.57, 7.54)
Any alert, set $PM_{2.5}$ = 25 μg/m^3	29.37	(-22.55, 81.29)
Orange Level ozone alert	-0.24	(-12.79, 12.31)
Red Level ozone alert	-27.86	(-71.22, 15.51)
Fills of Short-Acting Beta-Agonists (SABA)		
Increase ozone from 70 to 90 ppb		
Days WITHOUT an ozone alert	-1.76	(-4.99, 1.38)
Days WITH an ozone alert	-6.56	(-23.89, 17.23)
Increase $PM_{2.5}$ from 15 to 25 μg/m^3		
Days WITHOUT an ozone alert	**6.69**	**(2.77, 10.59)**
Days WITH an ozone alert	26.54	(-16.84, 89.58)
Any ozone alert, orange level or higher	4.4	(-27.65, 72.52)
Any alert, set ozone = 90 ppb	1.94	(-14.66, 22.81)
Any alert, set $PM_{2.5}$ = 25 μg/m^3	30.74	(-3.37, 78.37)
Orange Level ozone alert	**15.84**	**(5.97, 26.61)**
Red Level ozone alert	-9.33	(-35.82, 47.66)
Diabetes Office Visits		
Increase ozone from 70 to 90 ppb		
Days WITHOUT an ozone alert	-3.92	(-8.43, 0.72)
Days WITH an ozone alert	-19.76	(-45.12, 18.51)
Increase $PM_{2.5}$ from 15 to 25 μg/m^3		
Days WITHOUT an ozone alert	4.79	(-1.26, 10.64)
Days WITH an ozone alert	-4.02	(-47.79, 68.92)
Any ozone alert, orange level or higher	43.79	(-26.92, 236.31)
Any alert, set ozone = 90 ppb	8.91	(-18.8, 55.48)
Any alert, set $PM_{2.5}$ = 25 μg/m^3	29.46	(-21.56, 200.81)
Orange Level ozone alert	3.95	(-13.9, 23.59)
Red Level ozone alert	38.55	(-27.93, 211.8)

The percent change in outcomes and 95% confidence intervals were generated using bootstrapping techniques (10,000 repetitions) with confidence intervals from the bias-corrected percentile approach. The interacted model specifies air pollutants and ozone as : ozone + pm + (oz*pm) + orange + red + (ozone*orange) + (ozone*red) + (pm*orange) + (pm*red). All values of ozone, fine particulates (pm), ozone alerts (orange and red) and weather were measured on the previous day. A negative binomial count model was estimated for each of the outcomes, shown in the Appendix (Table A-10 and Table A-11). Weather was measured by a polynomial of temperature and relative humidity, precipitation and an indicator for hail or thunder. Other controls variables were day of week, month, and number of subjects eligible for the outcome. These results are shown graphically as a dose-response relationship in Figure 4-12 and Figure 4-13.

Table 4-15. Lag -3 to +3 models of asthma ER visits and inpatient stays, percent change in outcome associated with an increase in air pollution and ozone alerts

	Asthma ER visits			Asthma inpatient stays		
	Estimate, %	(95% CI, %)		Estimate, %	(95% CI, %)	
Ozone (8-hr), impact of 20 ppb increase						
lag -3	-3.9%	(-9.7%,	1.8%)	8.6%	(-0.7%,	17.9%)
lag -2	-4.9%	(-11.7%,	2.0%)	**-13.0%**	**(-21.8%,**	**-4.2%)**
lag -1	4.5%	(-3.4%,	12.4%)	**19.6%**	**(6.2%,**	**32.9%)**
lag 0	-0.1%	(-7.6%,	7.4%)	-4.6%	(-14.6%,	5.4%)
lag 1	-3.6%	(-10.7%,	3.5%)	3.9%	(-7.1%,	14.8%)
lag 2	0.4%	(-6.9%,	7.7%)	-0.6%	(-10.7%,	9.4%)
lag 3	-0.4%	(-6.4%,	5.6%)	**-8.4%**	**(-15.9%,**	**-0.9%)**
Fine Particulates, impact of 10 µg/m3 increase						
lag -3	5.7%	(-5.4%,	16.7%)	3.3%	(-11.8%,	18.4%)
lag -2	2.9%	(-10.0%,	15.8%)	-8.4%	(-24.9%,	8.1%)
lag -1	-4.2%	(-14.5%,	6.2%)	-0.7%	(-16.6%,	15.2%)
lag 0	-5.7%	(-16.2%,	4.7%)	3.5%	(-13.2%,	20.2%)
lag 1	2.1%	(-8.8%,	13.0%)	0.7%	(-14.6%,	16.0%)
lag 2	1.0%	(-11.0%,	13.0%)	-9.0%	(-24.5%,	6.6%)
lag 3	4.2%	(-5.8%,	14.1%)	6.6%	(-7.9%,	21.2%)
Orange Ozone Alert						
lag -3	3.8%	(-7.9%,	15.5%)	0.6%	(-15.2%,	16.4%)
lag -2	1.4%	(-10.9%,	13.7%)	-1.4%	(-18.3%,	15.6%)
lag -1	-3.5%	(-15.3%,	8.2%)	**-16.2%**	**(-30.9%,**	**-1.5%)**
lag 0	0.7%	(-11.3%,	12.7%)	-4.2%	(-20.2%,	11.8%)
lag 1	2.8%	(-9.4%,	15.0%)	9.8%	(-8.3%,	27.8%)
lag 2	4.1%	(-8.1%,	16.3%)	1.6%	(-15.4%,	18.6%)
lag 3	2.6%	(-8.9%,	14.1%)	4.9%	(-11.7%,	21.5%)
Red/purple Ozone Alert						
lag -3	-9.6%	(-29.3%,	10.0%)	11.5%	(-21.6%,	44.6%)
lag -2	13.1%	(-12.8%,	39.0%)	0.6%	(-33.1%,	34.4%)
lag -1	-15.0%	(-35.2%,	5.3%)	**-27.6%**	**(-52.3%,**	**-2.8%)**
lag 0	12.9%	(-12.6%,	38.4%)	-0.9%	(-33.0%,	31.1%)
lag 1	1.0%	(-22.2%,	24.2%)	16.7%	(-21.1%,	54.5%)
lag 2	4.1%	(-19.5%,	27.7%)	-9.0%	(-39.5%,	21.6%)
lag 3	7.2%	(-15.0%,	29.3%)	20.5%	(-14.7%,	55.8%)

The estimates and 95% confidence intervals were estimated using the delta method, implemented in STATA using the prvalue command. Estimates that were statistically significantly different from zero at 95% confidence levels are in **bold**. Regression coefficients and standard errors are shown in Table A-12. ER visits was modeled using the negative binomial model and inpatient stays with the poisson model. Lags -3 to +3 of weather were included as control variables, plus controls for month, day of week, and federal holidays. Apparent temperature, instead of the polynomial of temperature and humidity, was used as a control variable.

Table 4-16. Lag -3 to lag +3 models of office visits, percent change associated with an increase in air pollution and ozone alerts

	Asthma Office Visits			Diabetes Office Visits		
	Estimate, %	(95% CI, %)		Estimate, %	(95% CI, %)	
Ozone (8-hr), impact of 20 ppb increase						
lag -3	-1.6%	(-5.9%,	2.8%)	-1.2%	(-6.1%,	3.7%)
lag -2	-2.7%	(-7.9%,	2.6%)	-3.2%	(-9.0%,	2.7%)
lag -1	-0.9%	(-6.3%,	4.5%)	-1.4%	(-7.3%,	4.6%)
lag 0	3.2%	(-2.3%,	8.8%)	5.9%	(-0.5%,	12.3%)
lag 1	-3.0%	(-8.1%,	2.1%)	**-7.1%**	**(-12.5%,**	**-1.8%)**
lag 2	1.2%	(-4.1%,	6.5%)	0.1%	(-5.7%,	5.9%)
lag 3	0.3%	(-4.0%,	4.6%)	1.2%	(-3.7%,	6.1%)
Fine Particulates, impact of 10 µg/m3 increase						
lag -3	**12.3%**	**(3.7%,**	**20.9%)**	**11.3%**	**(1.7%,**	**21.0%)**
lag -2	-4.1%	(-13.1%,	4.9%)	-3.7%	(-13.9%,	6.6%)
lag -1	-2.4%	(-10.6%,	5.8%)	-5.0%	(-14.0%,	3.9%)
lag 0	-1.7%	(-10.1%,	6.8%)	-2.9%	(-12.3%,	6.5%)
lag 1	-1.5%	(-9.3%,	6.4%)	-1.3%	(-10.2%,	7.6%)
lag 2	3.6%	(-5.2%,	12.5%)	9.5%	(-1.1%,	20.0%)
lag 3	1.7%	(-5.2%,	8.7%)	4.0%	(-4.1%,	12.0%)
Orange Ozone Alert						
lag -3	-2.1%	(-10.2%,	6.0%)	2.8%	(-6.7%,	12.2%)
lag -2	4.0%	(-5.1%,	13.1%)	6.1%	(-4.2%,	16.4%)
lag -1	5.0%	(-4.0%,	14.0%)	4.5%	(-5.5%,	14.6%)
lag 0	-2.8%	(-11.3%,	5.6%)	-3.9%	(-13.3%,	5.4%)
lag 1	1.9%	(-7.0%,	10.9%)	2.5%	(-7.4%,	12.4%)
lag 2	0.9%	(-7.9%,	9.7%)	3.1%	(-6.9%,	13.1%)
lag 3	0.6%	(-7.7%,	8.9%)	-1.1%	(-10.3%,	8.1%)
Red/purple Ozone Alert						
lag -3	-4.3%	(-17.9%,	9.2%)	-3.1%	(-18.4%,	12.1%)
lag -2	9.9%	(-7.2%,	27.1%)	6.0%	(-12.7%,	24.7%)
lag -1	2.8%	(-13.3%,	18.9%)	8.5%	(-10.5%,	27.5%)
lag 0	-11.1%	(-25.1%,	2.9%)	-11.3%	(-26.7%,	4.2%)
lag 1	-5.4%	(-20.3%,	9.5%)	-11.1%	(-26.6%,	4.4%)
lag 2	**20.5%**	**(1.5%,**	**39.5%)**	29.4%	(6.6%,	52.2%)
lag 3	**-14.4%**	**(-27.0%,**	**-1.8%)**	-3.4%	(-18.9%,	12.1%)

The estimates and 95% confidence intervals were estimated using the delta method, implemented in STATA using the prvalue command. Estimates that were statistically significantly different from zero at 95% confidence levels are in **bold**. Regression coefficients and standard errors are shown in Table A-12. Visits were modeled using the negative binomial count. Lags -3 to +3 of weather were included as control variables, plus controls for month, day of week, and federal holidays. Apparent temperature, instead of the polynomial of temperature and humidity, was used as a control variable.

Table 4-17. Lag -3 to +3 models of drug fills, percent change associated with an increase in air pollution and ozone alerts

	OSC fills			SABA fills		
	Estimate, %	95% CI, %		Estimate, %	95% CI, %	
Ozone (8-hr), impact of 20 ppb increase						
lag -3	-3.1%	(-6.9%,	0.8%)	-0.1%	(-3.2%,	3.0%)
lag -2	3.2%	(-2.0%,	8.3%)	1.4%	(-2.5%,	5.2%)
lag -1	-1.1%	(-6.0%,	3.8%)	**-3.8%**	**(-7.5%,**	**-0.2%)**
lag 0	2.9%	(-2.2%,	7.9%)	2.3%	(-1.6%,	6.2%)
lag 1	-4.5%	(-9.0%,	0.1%)	-3.6%	(-7.1%,	0.0%)
lag 2	-2.4%	(-7.0%,	2.1%)	1.0%	(-2.7%,	4.7%)
lag 3	3.1%	(-1.0%,	7.2%)	-0.5%	(-3.5%,	2.6%)
Fine Particulates, impact of 10 µg/m3 increase						
lag -3	3.4%	(-3.7%,	10.6%)	4.4%	(-1.4%,	10.1%)
lag -2	1.1%	(-7.4%,	9.6%)	-1.4%	(-8.0%,	5.2%)
lag -1	2.1%	(-5.4%,	9.5%)	-1.2%	(-6.9%,	4.5%)
lag 0	-1.5%	(-8.9%,	5.9%)	0.3%	(-5.5%,	6.1%)
lag 1	-1.2%	(-8.2%,	5.8%)	0.4%	(-5.3%,	6.0%)
lag 2	5.8%	(-2.4%,	14.0%)	3.2%	(-3.0%,	9.4%)
lag 3	-3.0%	(-9.1%,	3.0%)	0.1%	(-4.7%,	4.9%)
Orange Ozone Alert						
lag -3	-3.9%	(-11.2%,	3.4%)	1.5%	(-4.4%,	7.4%)
lag -2	1.0%	(-7.0%,	9.1%)	1.7%	(-4.5%,	7.9%)
lag -1	0.4%	(-7.5%,	8.3%)	**7.1%**	**(0.7%,**	**13.5%)**
lag 0	-2.4%	(-10.1%,	5.4%)	1.3%	(-4.8%,	7.5%)
lag 1	3.4%	(-4.8%,	11.6%)	3.5%	(-2.8%,	9.7%)
lag 2	4.2%	(-4.0%,	12.4%)	0.5%	(-5.6%,	6.6%)
lag 3	-2.8%	(-10.1%,	4.5%)	3.9%	(-2.1%,	9.8%)
Red/purple Ozone Alert						
lag -3	-5.9%	(-18.6%,	6.8%)	2.1%	(-8.0%,	12.3%)
lag -2	0.9%	(-14.0%,	15.8%)	-3.2%	(-13.8%,	7.5%)
lag -1	1.7%	(-13.0%,	16.5%)	2.5%	(-8.8%,	13.8%)
lag 0	-4.8%	(-18.7%,	9.0%)	-1.5%	(-12.3%,	9.3%)
lag 1	8.9%	(-6.9%,	24.6%)	-1.6%	(-12.4%,	9.2%)
lag 2	14.9%	(-1.7%,	31.6%)	**12.3%**	**(0.2%,**	**24.5%)**
lag 3	-8.4%	(-20.9%,	4.1%)	-2.7%	(-12.5%,	7.0%)

Notes: . The estimates and 95% confidence intervals were estimated using the delta method, implemented in STATA using the prvalue command. Estimates that are statistically significantly different from zero at 95% confidence levels are in **bold**. Regression coefficients and standard errors are shown in Table A-13. Drug fills were modeled using the negative binomial count model. Lags -3 to +3 of weather were included as control variables, plus controls for month, day of week, and federal holidays. Apparent temperature, instead of the polynomial of temperature and humidity, was used as a control variable for brevity.

Results Figures

Figure 4-1. Distribution of asthma ER visits and inpatient stays

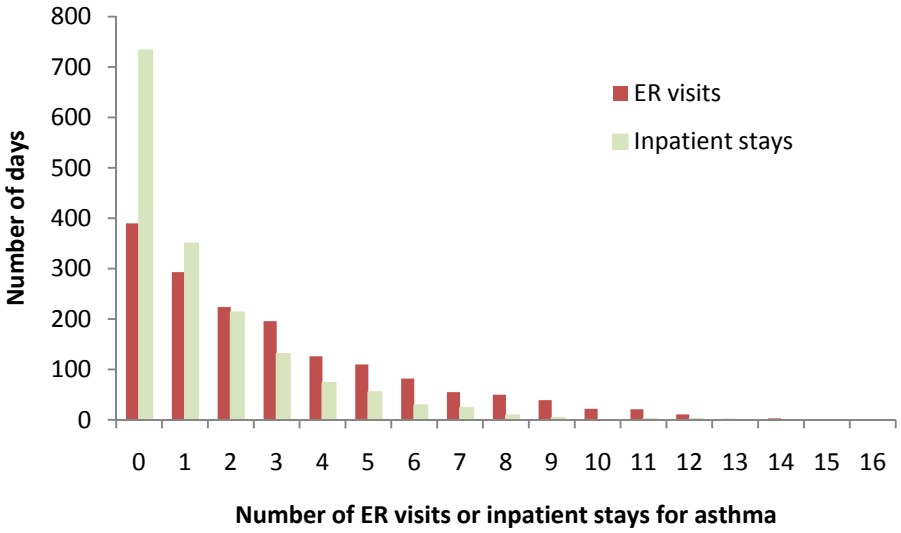
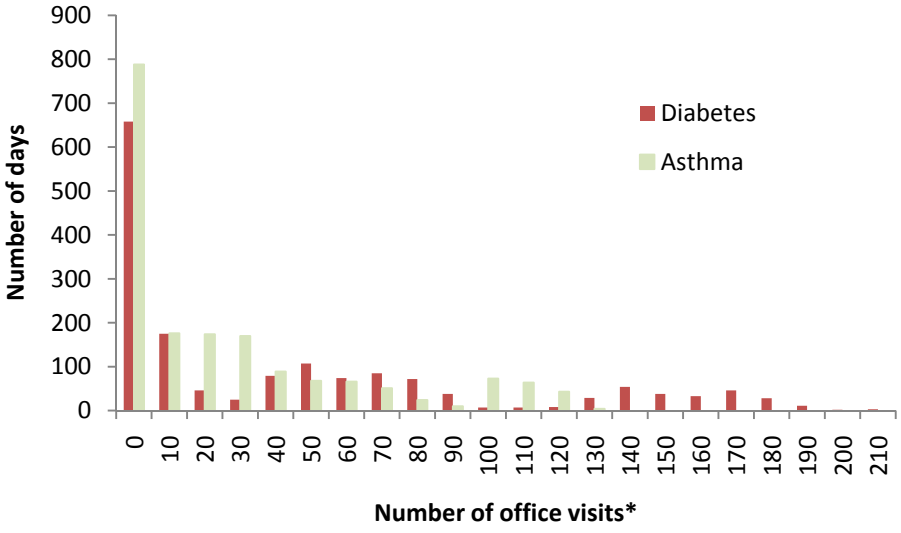
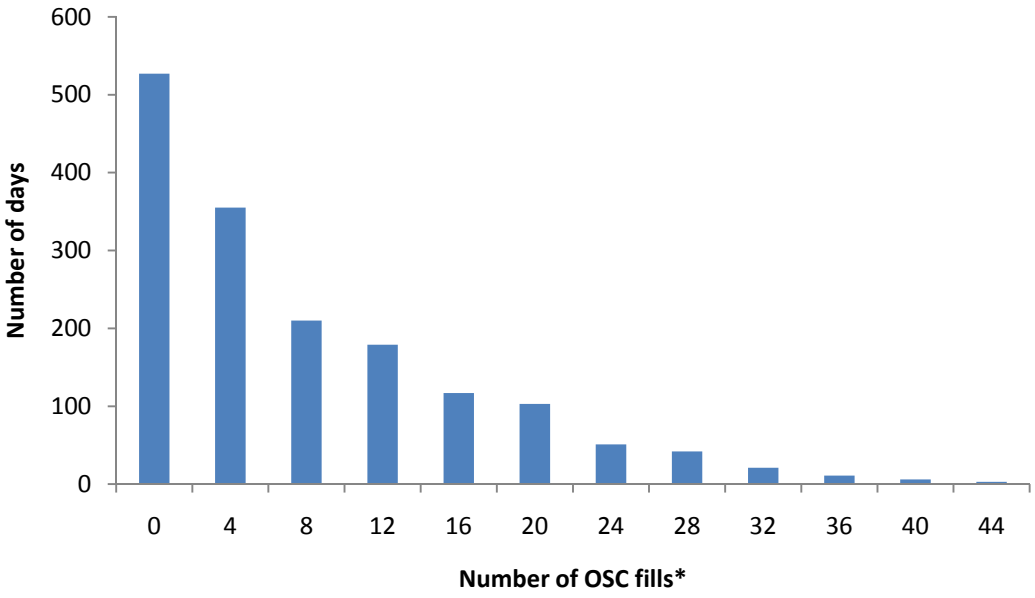


Figure 4-2. Distribution of asthma and diabetes office visits



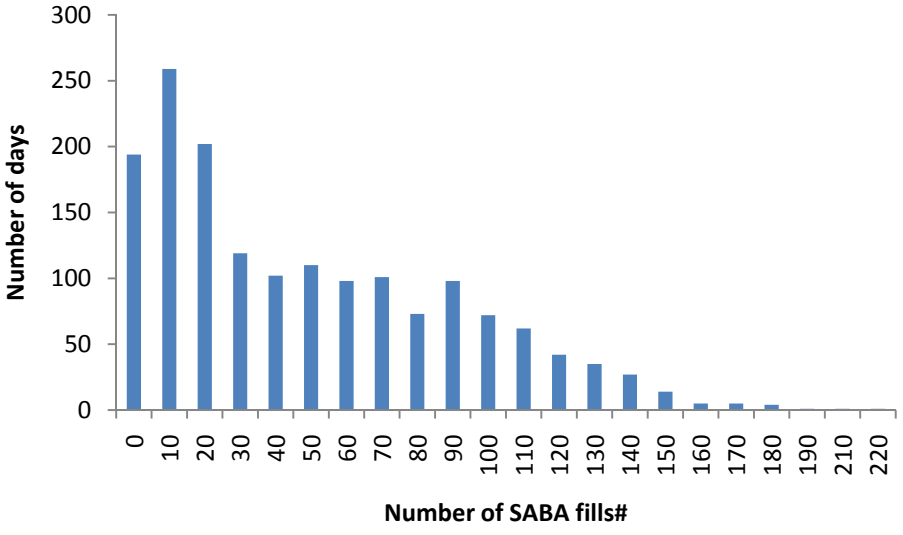
* Bin size=10 visits so first pair of bars represents 0-9 visits

Figure 4-3. Distribution of Oral Systemic Corticosteroid (OSC) fills



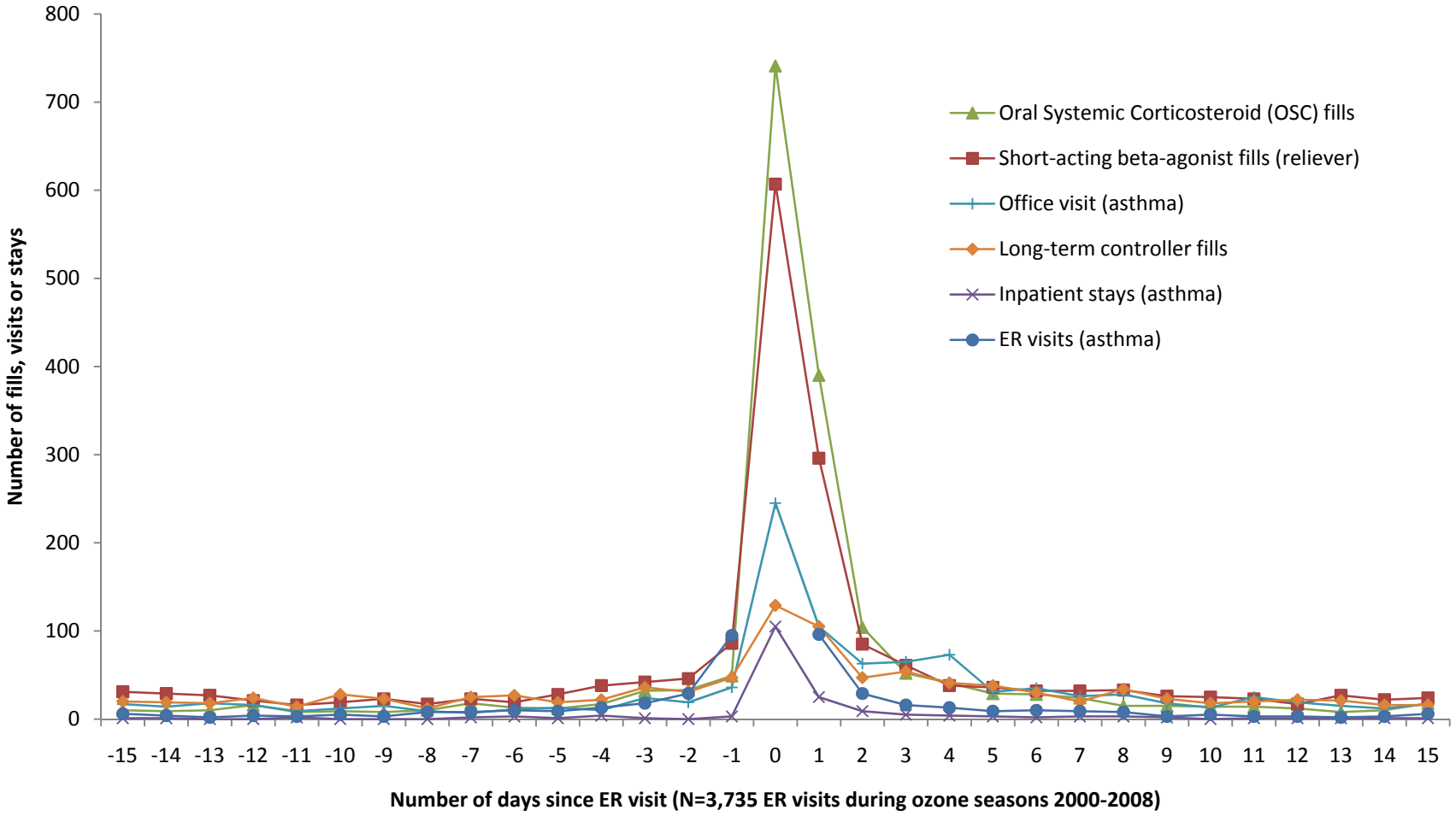
* Bin size= 4, so first bar represents days with 0-3 fills, second bar is 4-7 fills etc.

Figure 4-4. Distribution of Short-Acting Beta-Agonist (SABA) fills



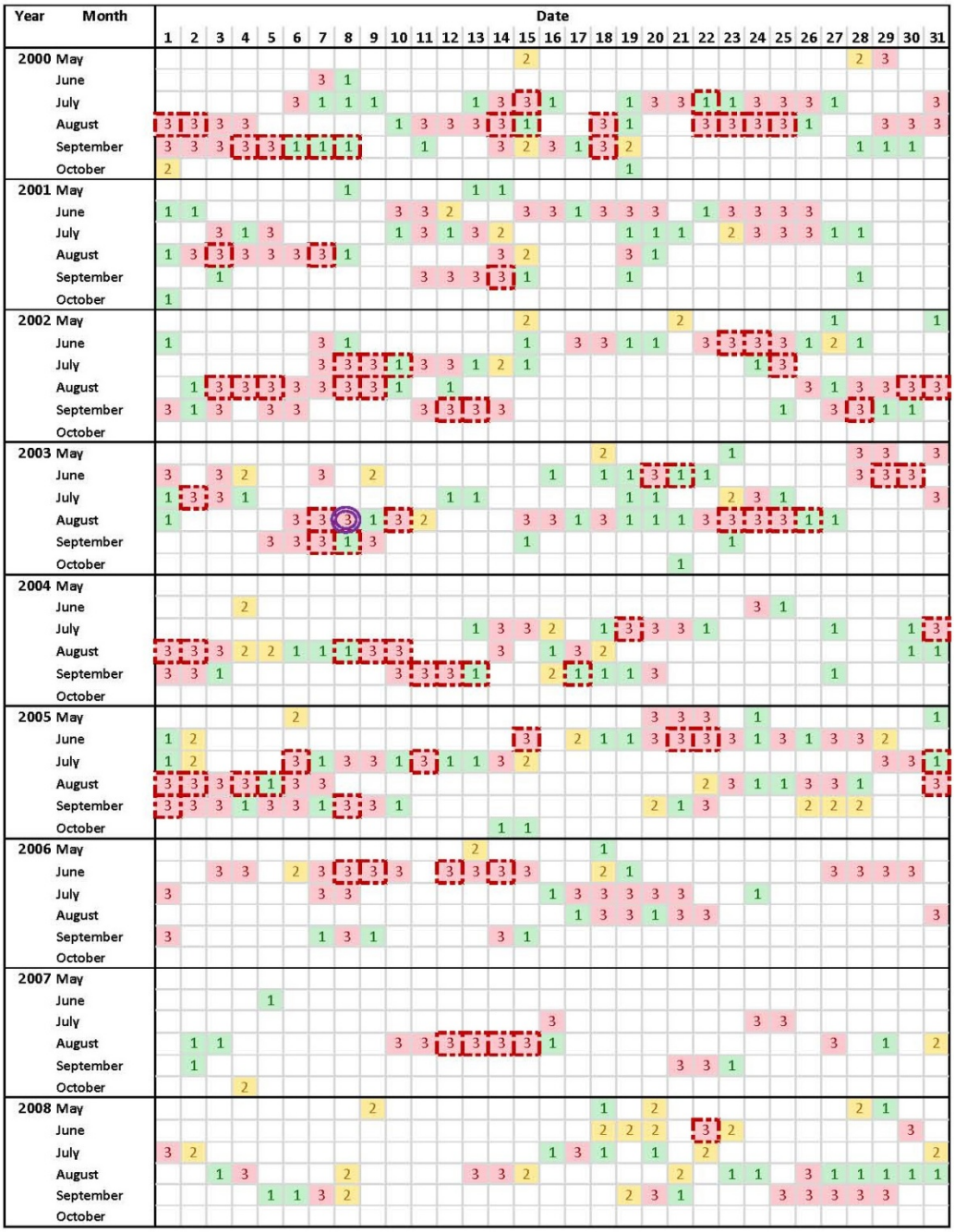
Bin size= 10 fills, so first far represents days with 0-9 fills, second bar is 10-19 fills etc.

Figure 4-5. Fills, visits, and stays within 15 days before and after an asthma ER visit



The data point of 3,735 ER visits at t=0 is omitted from the figure to show the features of the other outcomes more clearly.

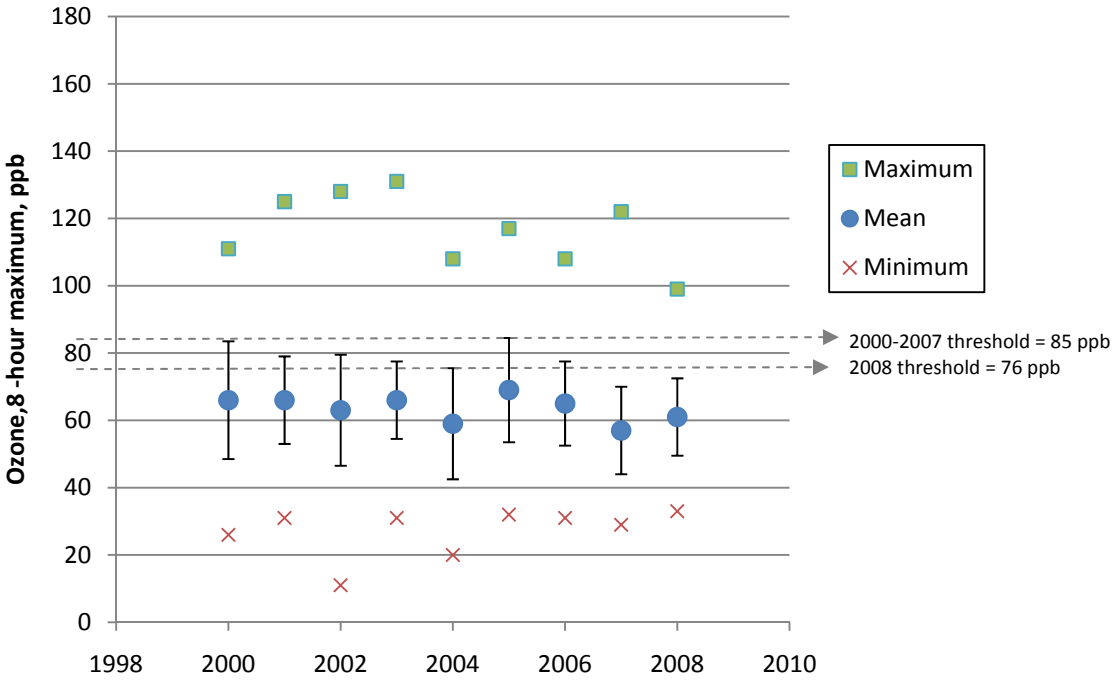
Figure 4-6. Pattern of ozone alerts and days ozone levels actually exceeded target levels



Legend		
	3	Orange or higher alert issued and target* value achieved
	2	No alert issued, but target* value achieved
	1	Orange level or higher alert issued, but target* value not achieved
		No alert and did not exceed target* value
		Red level ozone alert issued
		Purple level ozone alert issued

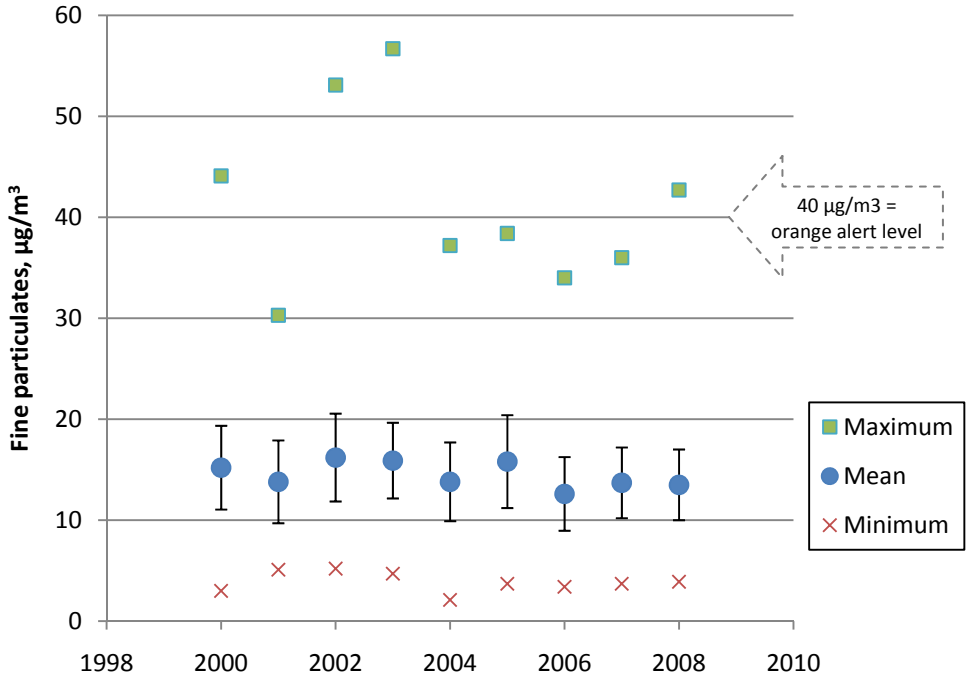
* Target value for orange alerts of higher was 85 ppb for 8-hour ozone for 2000-2007. In 2008 this was lowered to 76 ppb (8-hour). The target value for red alerts was 105 ppb prior to 2008 and 96 in 2008. The target value for purple alerts was 125 ppb prior to 2008 and 116 in 2008.

Figure 4-7. Ozone levels each season



The ozone season is May – October each year. The error bars around the mean indicate the interquartile range of values (25th and 75th percentiles).

Figure 4-8. Fine particulate levels each year 2000-2008



The ozone season is May – October each year. Orange Level thresholds are shown for reference only ; fine particulate alerts are not issued in Dallas-Fort Worth. The error bars around the mean indicate the interquartile range of values (25th and 75th percentiles).

Figure 4-9. Correlation coefficients between each lag of ozone and fine particulates

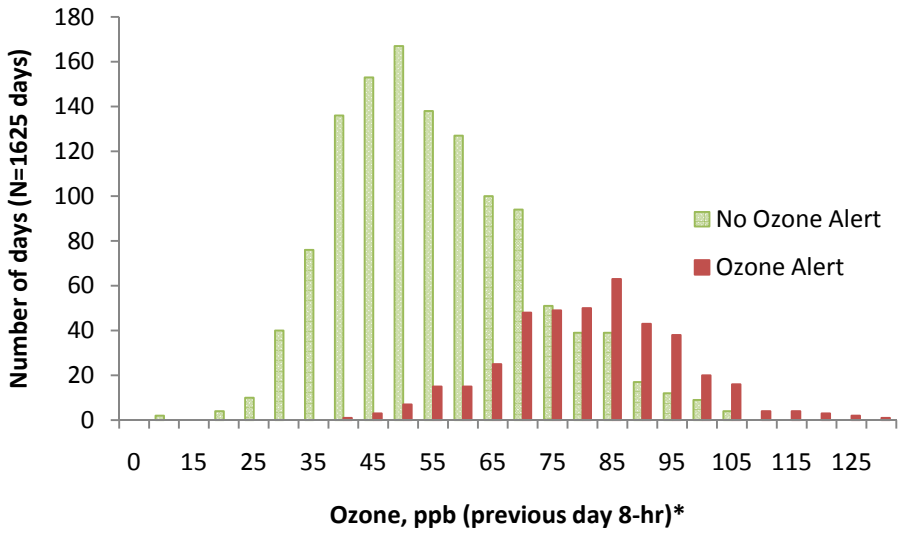
		Ozone (8-hr), ppb								
		-4	-3	-2	-1	0	1	2	3	4
Ozone (8-hr), ppb	-4	1.00								
	-3	0.74	1.00							
	-2	0.48	0.74	1.00						
	-1	0.34	0.49	0.74	1.00					
	0	0.25	0.34	0.49	0.74	1.00				
	1	0.18	0.25	0.35	0.49	0.74	1.00			
	2	0.17	0.19	0.26	0.35	0.50	0.75	1.00		
	3	0.15	0.17	0.20	0.27	0.36	0.50	0.75	1.00	
	4	0.13	0.16	0.18	0.20	0.27	0.36	0.51	0.75	1.00
Fine particulates	-4	0.26	0.38	0.47	0.43	0.31	0.22	0.16	0.13	0.11
	-3	0.23	0.33	0.45	0.46	0.33	0.22	0.16	0.13	0.11
	-2	0.20	0.29	0.42	0.48	0.38	0.26	0.19	0.16	0.13
	-1	0.19	0.26	0.39	0.48	0.42	0.30	0.21	0.15	0.12
	0	0.13	0.22	0.33	0.46	0.50	0.36	0.25	0.19	0.14
	1	0.09	0.18	0.28	0.40	0.49	0.43	0.32	0.24	0.18
	2	0.08	0.15	0.25	0.36	0.46	0.46	0.34	0.24	0.18
	3	0.06	0.12	0.20	0.30	0.41	0.45	0.36	0.25	0.18
	4	0.07	0.15	0.21	0.29	0.40	0.45	0.40	0.29	0.20

	Fine particulates (daily), µg/m3								
	-4	-3	-2	-1	0	1	2	3	4
-4	1.00								
-3	0.83	1.00							
-2	0.71	0.87	1.00						
-1	0.59	0.74	0.85	1.00					
0	0.48	0.56	0.66	0.78	1.00				
1	0.39	0.45	0.53	0.63	0.81	1.00			
2	0.35	0.42	0.47	0.55	0.68	0.84	1.00		
3	0.30	0.35	0.40	0.46	0.57	0.71	0.86	1.00	
4	0.27	0.31	0.35	0.41	0.51	0.61	0.74	0.84	1.00

Legend	
1.00	Perfectly correlated
0.75	
0.50	
0.25	
0.00	Not correlated

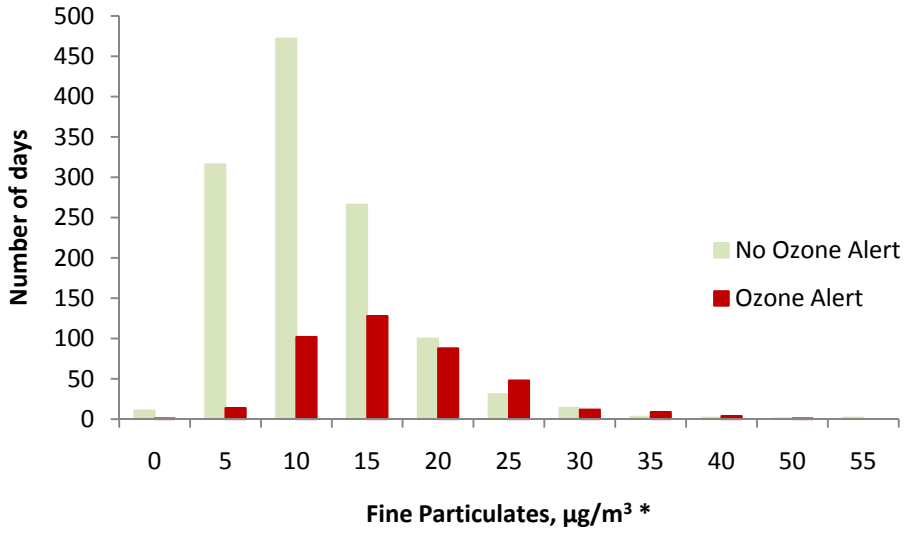
Correlation coefficients were calculated using STATA's correlate command. All of the correlations were statistically significant at 99% confidence levels, except for the correlation between lag -3 of fine PM and lag -4 of ozone which was statistically significant at 95% confidence levels.

Figure 4-10. Distribution of ozone levels, by days with and without an ozone alert



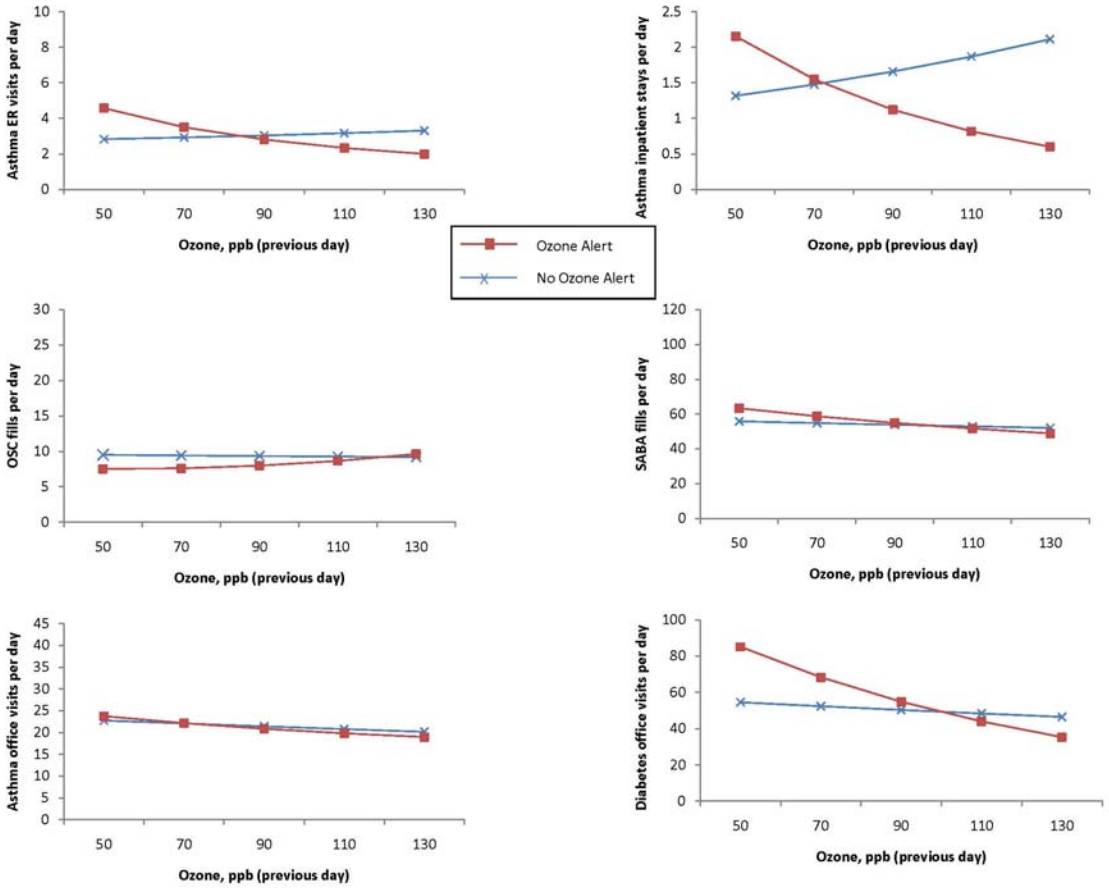
* Bins are 5 ppb wide, so the first bin on the left includes days with 5-9 ppb concentration of ozone
Ozone alerts are orange level or higher

Figure 4-11. Distribution of fine particulate levels, by days with and without an ozone alert



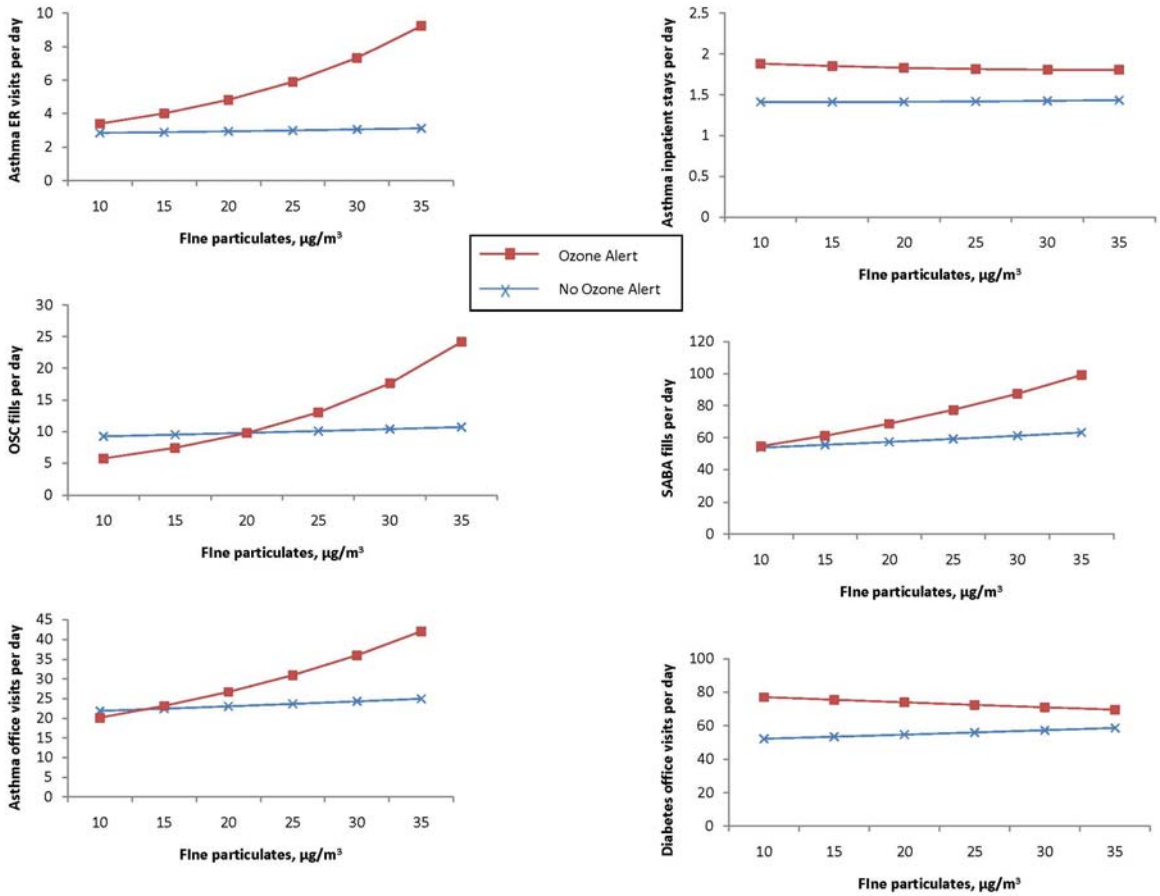
* Bin size is 5 µg/m^3, so the first bar on the left includes days with concentration of 0-4 µg/m^3
Ozone alerts are orange level or higher

Figure 4-12. Dose-response relationships for ozone, interacted model



Notes : Confidence intervals for marginal effects are shown in Table 4-14. Coefficients are shown in Appendix Table A-10 and Table A-11

Figure 4-13. Dose-response relationships for fine particulates, interacted model



Notes: Confidence intervals for marginal effects are shown in Table 4-14. Coefficients are show in Appendix Table A-10 and Table A-11.

Chapter 5 Discussion

Summary of Findings

This study found evidence that ozone alert are protective and ignoring them may underestimate the effect of poor air quality in observational studies. The strongest results were found for acute events (asthma inpatient stays and ER visits). Increases in ozone were associated with worse asthma outcomes and ozone alerts were associated with better outcomes for both ER visits and inpatient stays. These associations were consistently statistically significant for inpatient stays. For the lower morbidity outcomes (asthma office visits, OSC fills, and SABA fills), these relationships were not consistently observed, although the lag models suggest that subjects may fill their quick-relief medications in advance of poor quality days (red alerts) and may go to their doctor's office as follow-up after poor air quality days.

Asthma Inpatient Stays

A protective effect of previous day ozone alerts was consistently observed for asthma inpatient stays. Higher alert levels (red or purple) were associated with a stronger protective effect of ozone alerts than lower alert levels (orange). Orange level ozone alerts were associated with 14.1% (base model) to 26.8% (Model 3 of sensitivity analysis) fewer asthma inpatient stays. This association was statistically significant at 95% confidence levels in all specifications, except for the models by age group which only achieved statistical significance for ozone for adults. Red or higher ozone alerts were associated with 19.9% (base model) to 35.5% (Model 3 of sensitivity analysis) fewer asthma inpatient stays and was statistically significant in many specifications.

Ignoring information about ozone alerts underestimated the harmful effect of ozone by about 40% for asthma inpatient stays ((11.6%-7.0%)/11.6%=.40). When

controls for ozone alerts were included, a 20 ppb increase in previous day ozone levels was associated with 9.1% (base model without fine particulates) to 16.5% (model 1 of sensitivity analysis) more asthma inpatient stays and this association was often statistically significant.

These associations were consistent in all specifications with the single lag, except for the 2005 asthma cohort (model #5 of the sensitivity analysis). For the 2005 asthma cohort, increases in ozone were associated with fewer inpatient stays, although this was not statistically significant. Ozone alerts were associated with inpatient stays in a protective way, but this was much smaller than effects in the general sample and no longer statistically significant. The sign on fine particulates was opposite for the 2005 asthma cohort, although fine particulates were not statistically significant in any of the specifications of inpatient stays. The 2005 asthma cohort differs from the general sample in that it had a much lower rate of inpatient stays (Table 4-6). There were only 721 inpatient stays in the 2005 asthma cohort, thus the finding for the 2005 asthma cohort could be a random anomaly related to small sample size. Subjects in the 2005 asthma cohort likely had better access to drugs because they had a higher fraction of subjects enrolled in a drug plan. Subjects not enrolled in a drug plan likely had to pay more out of pocket for drugs, which can lead to lower use of drugs and may be correlated more generally to poorer access to primary care. Furthermore, of those enrolled in drug benefits, subjects in the 2005 asthma cohort also were more likely to have fills of long-term asthma controller medications than subjects with asthma in the general sample. Long-term controllers are inhalers that are taken daily and are intended to lessen asthma exacerbations and lower the use of the quick-reliever inhalers, ER visits and inpatient stays. Thus it may not have been random that the 2005 asthma cohort found counterintuitive results for ozone. These subjects used more controllers and had more asthma office visits which may have weakened the link between ozone, ozone alerts and inpatient stays.

Ozone was more strongly related to more inpatient stays for adults than for children. The harmful association between an increase in ozone and fine particulates

was more than twice as large for adults than for children. The relationship between ozone and inpatient stays was statistically significant for adults but not children. This may be due to the fact that children use inpatient care for asthma at lower rate than adults (Table 4-5). Thus the sample of inpatient visits for children is smaller and subject to more noise. Children tend to use inpatient care less because the typical child has less severe (i.e. not life-threatening) asthma attacks than adults.

The -3 to +3 lag models that related past and future lags of ozone, fine particulates, ozone alerts and weather supported the main specification which related inpatient stays to previous day air pollution and ozone alerts. The previous day lags on orange and red or higher alerts were the only lags that were statistically significant. For ozone, multiple lags were significantly associated with inpatient stays: lag -2 (negative association), lag -1 (positive association, also the largest) and lag +3 (negative association).

In the interacted model, increases in ozone were more harmful on days without an ozone alert. Ozone alerts appeared to be even more protective the worse the actual ozone level, likely because people may respond more strongly to the higher level (red alerts) that is associated with higher ozone levels. However, since overlap in ozone levels on days with and without ozone alerts is limited (Figure 4-10), results are likely sensitive to days at each extreme (low ozone days with an ozone alert and high ozone days without an ozone alert).

Asthma ER visits

Results for asthma ER visits are supportive of the hypotheses about ozone and ozone alerts, although results were not statistically significant. A 20 ppb increase in previous day ozone levels was associated with 0.7%-6.2% more asthma ER visits. Limiting the data to only 2002-2006 yielded the highest estimate on ozone, likely due to the fact that the middle years had worse air quality than the years at the start and end of the time series. Orange level ozone alerts were associated with 3.8% to 9.7% fewer asthma ER visits in the previous day models. While ozone had a stronger relationship with inpatient stays for adults than for children, ozone and ozone alerts had a stronger

association with asthma ER visits for children than for adults. This is likely due to similar reasons as before. Children tend to use the emergency room more than adults, but have less serious cases so they usually don't need to be admitted to the hospital. One could argue that ER visits are not totally avoidable even if primary care was "perfect" – asthma attacks will occur outside of doctors hours (evenings, weekends and holidays), necessitating some care in the ER. The lower use of the ER by adults may make the analysis of adults more susceptible to noise related to visits that had little to do with the environmental trigger and had more to do with the fact that their doctor's office was not open.

Results from the -3 to +3 lag models were difficult to interpret for asthma ER visits. Past lags of ozone were more negative (helpful) than positive (harmful). Most of the lags of ozone alerts were positive (harmful), except for the previous day lags, although none of these associations were statistically significant.

Results for ozone for previous day models with pollution-alert interactions for ER visits were qualitatively similar to same model of inpatient stays. Increases in ozone were harmful on days without alerts but increases in ozone on days with alerts were actually protective, suggesting that ozone alerts were more protective the worse the actual air quality. This could be due to the simple reason that ozone alerts on low air quality days should not have much of an impact, simply because there is little harm that is being avoided. There also could be a behavioral interaction going on for days with poor actual air quality if subjects monitor actual air quality as well as the ozone alerts. People can register for email alerts about actual air quality levels and check levels online and may be more diligent about avoiding outdoor exercise in the afternoons when they see that high ozone levels have already been achieved during the day. The interacted model of ER visits differed from that of inpatient stays in that increases in ozone on days without alerts were associated with smaller increases in ER visits. This is consistent with what I observed in the non-interacted models; the association between ER visits and ozone was much smaller than the association between inpatient stays and ozone.

Asthma Outpatient visits

Findings for asthma outpatient visits were mixed, although strong relationships between ozone, ozone alerts and outpatient visits were not hypothesized. While I would expect people to visit the doctor for asthma more often when the air quality is poor, the relationship in time may not be tight. For example, a subject may go to the doctor after a high ozone episode to adjust their asthma medications. There is some evidence that people may see their doctor after red or higher level ozone alerts.

The only model of outpatient visits that found both a harmful association with ozone and a protective association with ozone alerts were the two models that did not control for seasonality (Model 4 and 5 of the sensitivity analysis in Table 4-12). Results were also sensitive to the years of data that were included. Asthma outpatient visits may be more sensitive to the specification of seasonality and data years since the temporal link between asthma exacerbations and visits is weaker than the link for ER visits and inpatient stays. Thus, the decision about whether this monthly variation during the ozone season is a confounder becomes more important. It is not entirely clear whether this monthly variation is a confounder or is a part of the variation of ozone levels that is important to identifying the association between ozone and asthma exacerbations. Ozone levels vary during the summer, with more high ozone days occurring in July and August (Figure 4-6 and Table 4-10), due to weather patterns and larger amounts of solar radiation during long summer days that converts more of the source pollutants into ozone. Asthma exacerbations are also strongly related to the school year, especially in children and adults who care for them. Upper respiratory infections are common when children return to school in September and these can complicate an asthma attack and turn a relatively minor asthma exacerbation into one needing inpatient care. With the controls for seasonality, ideally I would like to control for the school year patterns in asthma exacerbations, but not for the natural variation in ozone levels that occurs during the long summer days.

Diabetes Office Visits

Diabetes office visits were included as a falsification test because diabetes office visits are not expected to be related to ozone levels. However, results for asthma office

visits and diabetes office visits were often quite similar, suggesting that other factors, beyond ozone and ozone alerts, may be driving the observed patterns in office visits. Office visits, both asthma and diabetes, primarily can occur only during business hours on normal work days since many doctors' offices are closed outside of normal business hours. However, ozone levels are correlated with work days due to the fact that economic activity (transportation, factories) contribute to the source pollutants that are transformed into ozone by sunlight. Ozone levels and ozone alerts were positively correlated with days later in the week as pollution levels accumulated as part of the weekly economic activity. Ozone levels were negatively correlated with Sundays and federal holidays (Table 4-10). This may be why diabetes office visits also appear to be correlated with higher ozone and ozone alerts. Taken together, this suggests that results related to asthma office visits should be interpreted with caution. ER visits and inpatient stays are less susceptible to this confounding by day of week because hospitals and emergency rooms are open every day and access to them is not likely to be confounded with ozone levels.

Fills of Oral Systemic Corticosteroids (OSC)

I hypothesized that OSC fills would follow similar patterns as ER visits and inpatient stays since OSCs tend to be given for asthma primarily for emergency situations. It is systemic and taken orally, so works slower than the quick-acting inhalers (SABAs). OSCs are longer acting, but have more serious side effects than inhaled controllers since OSCs are taken into the whole body system and are not targeted to the lungs. Results were mixed in the same ways that results were mixed for asthma office visits. Associations were sensitive to the years of data included. The only models with associations in the hypothesized direction were the two models that did not control for monthly variation (Models 4 and 5 of the sensitivity analysis). The harmful association between ozone and OSC fills even achieved statistical significance in model for the asthma 2005 cohort. The analysis for the asthma 2005 cohort differed in an important way. Since everyone in the 2005 asthma cohort had asthma, a confirmatory diagnosis

on OSC fills was not necessary and was not required in the analysis. However, in the general sample, a confirmatory diagnosis was necessary and was required because most people did not have asthma. I required that OSC fills have a confirmatory asthma diagnosis in the same calendar year for the analysis of the general sample. In principle, subjects need to see a doctor to obtain a fill for an OSC or would likely have a follow-up visit if the prescription was obtained over the phone. Thus most OSC fills should also have an asthma diagnosis in the claims, if the OSC was to treat asthma. However, this approach may have been overly conservative and missed some OSC fills that were for asthma.

Results for OSC fills for the model that interacted ozone and ozone alerts were not consistent with associations observed for inpatient stays and ER visits. Increases in ozone levels on days without ozone alerts were associated with fewer OSC fills. On days with an ozone alert, increases in ozone were associated with more OSC fills, although red alerts were associated with a protective effect.

Short-acting beta-agonist (SABA) fills

Short-acting beta-agonists are quick-relief inhalers that asthma patients typically have on hand to self-treat asthma exacerbations at home. Again the temporal link between fills and asthma attacks is expected to be weaker for SABA fills than for ER visits, inpatient stays and OSC fills because subjects fill the drugs in advance of asthma attacks and typically obtain a supply expected to last at least a month. There is some evidence that SABA fills are related to ozone alerts, with more fills on days after ozone alerts. An orange alert on the previous day was associated with 5.9% to 8.5% more SABA fills and was statistically significant at 95% confidence intervals in many specifications. A red alert was associated with a smaller increase in SABA fills, 1.6% to 4.4% more fills. Since red alerts often occur later in a high ozone episode, it is likely that patients may respond to the initial orange alerts, but not the later red alerts since they already have supply of medications at home. In the lag models, orange ozone alerts on the previous day were significantly associated with 7.1% more fills and red or higher

alerts 2 days later we associated with 12.3% more fills, also significant at 95% confidence levels.

Fine particulates

The purpose of including a control for fine particulates was to assess if results were sensitive to the inclusion fine particulates. Clinical evidence is stronger for the harmful relationship between ozone and asthma, with less evidence for fine particulates and asthma. Clinical and epidemiological evidence typically links fine particulates with increased risk of stroke and heart attacks. It is also more difficult to identify the effect of fine particulates because concentrations of this pollutant are more persistent and slower moving over time, compared with ozone. Peak ozone levels are associated with days of strong sunlight and can fluctuate greatly during the course of a day or a week, providing a source of random variation for researchers. Furthermore, ozone breaks down quickly indoors and when it come into contact with surfaces, so it is easier to avoid ozone than fine particulates by going indoors. Fine particulates form from different reactions that do not depend on sunlight, so concentrations persist over time, which we can see in the correlations shown in Figure 4-9. The concentration of fine particulates indoors may not be that much lower than outside, if there is a lot of mixing of the air from indoors and outdoors. For Dallas, fine particulate levels were generally low, although there were a few days during the study that exceeded the orange alert level, although fine particulate alerts were not issued. Thus, I expect that fine particulate levels in Dallas-Fort Worth would probably be too low to detect any harmful association, even if there is a harmful association.

I found that results for ozone and ozone alerts were generally similar regardless of whether fine particulates were included in the regression. In some cases fine particulates were associated with more visits, fills or stays, and in other cases with fewer. Associations with fine particulates were not typically statistically significant, except for some of the drug models.

Comparison to previous work

The prevalence of treatment for asthma in this sample was 4.0 per 100 subjects, which is lower than prevalence rates based on survey responses since asthma is episodic and many asthmatics do not need to receive treatment each year by a doctor.

Healthcare utilization rates reported in this study were similar to national estimates. I found higher rates of annual use of asthma doctor office visits in the 2005 asthma cohort (78.1 per 100 with asthma) than national estimates (61.2 visits per 100 with asthma), although the rate in the main analysis was almost the same as national estimates (59.4 per 100 with asthma). Utilization of inpatient care for asthma was higher in this study (3.40 – 3.48 per 100 with asthma) than national estimates of 2.5 discharges per 100 with asthma. The annual rate of ER visits for the general sample was slightly lower than national estimates, finding 7.13 visits per 100, compared with 8.38 per 100 nationally (Moorman et al. 2007).

Larger differences in asthma care utilization rates were observed between national estimates and this study when comparing rates of each outcome by age. This study found that children with asthma used ER visits 16% more than adults, while national estimates have found a much larger difference. In national estimates, children use the ER 44% more than adults with asthma. One explanation is that I used slightly different age grouping to define adults and children. I excluded children under 5 and adults over 54 because asthma can be difficult to observe in medical claims data in the very young and over 54. Asthma may be confused with wheezing related to lung development, in the very young. Asthma and COPD can be difficult to separate in the over 54 group. This study found that adults used inpatient care more than double the rate of children. National estimates also have found that adults with asthma use inpatient care more than children, but find a smaller difference between the utilization rates by adults and children (Moorman et al. 2007). This study found that adults and children used outpatient asthma office visits at similar rates while national studies have found that children with asthma use doctor office visits 40% more than adults (Moorman et al. 2007).

Neidell (2009b) came to similar conclusions as this study that ozone alerts are protective and that ignoring this information biases conclusions about the health effects of ozone. However, he found effects only for children and the elderly, but not adults. This study found that ozone alerts were protective for both adults and children. Controlling for ozone alerts and a continuous measure of the air quality forecast increased the effect of ozone by 160% for children, 40% for elderly, with no effects on adults. Neidell controlled for CO and NO_2 level, but did not control for fine particulates, which may not have been available during his study period (1989-1997). Neidell did not report whether results were sensitive to the inclusion of controls for CO and NO_2.

In addition to finding that pollution had a larger effect on children/elderly; Neidell also found that children and the elderly were more responsive to ozone alerts (a larger protective effect). I find that inpatient stays by adults are more sensitive to ozone and ozone alerts but ER visits are more sensitive to ozone and ozone alerts for children, although these differences were not statistically significant. One explanation could be different definitions for discharges used in the datasets. I define inpatient stays as requiring an overnight stay, while the hospital discharges measured by Neidell may not have had this requirement. The exact definition of hospital discharges was not described in the paper. Another explanation could be differences in how the alerts are used in Dallas-Fort Worth and Los Angeles (Neidell study). California schools will cancel outdoor school activities, such as sports practices and games, on poor air quality days (Neidell 2008). I have not found evidence that similar school policies exist in Dallas-Fort Worth. Thus while children (or more likely their guardians) may have a stronger incentive to avoid exposure to poor air quality because they are more susceptible, they may not be able to if their daily activities are difficult to reschedule on poor air quality days. Activities by adults, such as outdoor exercise and yard work, may be easier to reschedule on a different day or choose an alternative activity (work out at an indoor gym).

Neidell (2009b) reported the daily number of visits in the study area (34.2 discharges daily), but no denominator is provided to calculate a rate of inpatient stays.

Assuming 16 million people live in the study area[4] and an asthma prevalence rate of 7.2 per 100 (Moorman et al. 2007), results reported by Neidell suggest an annual rate of inpatient stays for asthma of 1.1 discharges per 100, which is lower than the rate of 2.79 per 1,000 found in this study.

Few previous studies of asthmatics have examined the health effects of ozone and particulates simultaneously. This study finds that significant associations between asthma exacerbations and ozone are robust to the inclusion of controls for fine particulates, consistent with the few multipollutant studies of ozone and particulates. There are relatively few studies of $PM_{2.5}$ in the U.S. because $PM_{2.5}$ monitoring has become widespread only in the last decade. Ito et al. (2007) found a positive association with fine particulates and asthma hospitalizations by children in the warm season (New York, NY). Sarnat et al. (2008) report from the SOPHIA study in Atlanta, GA that $PM_{2.5}$ was associated with a 2-4% increase in respiratory hospital visits (Sarnat et al. 2008). Most non-US (primarily single city studies) have found evidence of an association between $PM_{2.5}$ and asthma exacerbations, although a few have not (EPA 2008). None of the existing studies of both $PM_{2.5}$ and ozone have considered adults under 65, focusing exclusively on children.

Lag relationships for air quality and asthma exacerbation are similar to what has been reported in literature for ER visits and inpatient stays, finding that the largest effects occur in the first lag. In this study, previous day had the largest effect. Neidell (2009b) reported the cumulative effect of ozone from 5 past lags on inpatient stays and did not report detail on the effects of other lags. Other studies comparing age groups found that longer lags (3-5 days) were important for children, but not adults, and where the largest effect was on the same day (lag 0) (Sinclair and Tolsma 2004).

Study contributions and limitations

This study has extended research on ozone alerts in a variety of ways. First, I examined a broader array of outcomes, compared to previous work which studied

[4] http://www.aqmd.gov/aqmd/index.html, accessed 3/10/2009

asthma hospitalizations. This study also found that ozone alerts were protective for both adults and children, whereas previous work had found an effect for children, but not adults.

I also examined whether there was a multiplicative effect of ozone alerts and ozone levels, using interaction models. These models appeared to suggest that ozone alerts were more protective at higher levels for asthma inpatient stays and ER visits. This is remarkable given that the bias due to less of overlap between ozone levels and ozone alerts at high levels would results in a biasing the protective effect of ozone alerts to zero. Since there were more days with low level ozone that never have alerts (11%) than high ozone days that always have alerts (less than 1%), days without an ozone alert were correlated with low ozone levels. This could bias the protective effect of ozone alerts upwards (more protective) and bias the harmful effect of ozone to zero, no health effect. Future work should examine the role of bias due to non-overlap, such as by conducting an analysis of only local effects of ozone alerts in the neighborhood of ozone levels where there is overlap between days with and without ozone alerts. Since the identification of the effect of ozone alerts requires that forecast errors are not systematically correlated with factors that are also correlated with asthma exacerbations, future work should test whether this condition typically holds. This could be examined by related forecast errors to a variety of variables used to generate forecasts and may be correlated with asthma exacerbations.

This study also examined both past and future lags of ozone and ozone alerts. The future lags are associated with anticipating behavior. I would not expect people to go to the ER or have an inpatient stay in anticipation of future high ozone levels. However, patients may fill their asthma medications or go to their doctor to renew their prescription to prepare for high ozone days. Results were difficult to interpret, likely because the patient's inventory of medications was not controlled in this study. Some people may only fill their rescue inhalers right when they need them, while others may purchase a 3-month supply to ensure that they always have sufficient medications on hand. Since additional use of asthma medication is a cost of poor air quality, future

work should attempt to measure increases in medication use, perhaps by using a longer time scale, instead of the daily variation in air quality that was used in this study.

This study also contributes new evidence on ozone alerts in Dallas-Fort Worth. This is the first study to study ozone alerts in Dallas-Fort Worth. Earlier studies of ozone alerts and avoidance behavior have been of Southern California (Bresnahan et al. 1997; Graff Zivin and Neidell 2009; Neidell 2009a; Neidell 2009b; Yen et al. 2004) and Salt Lake City, Utah (McDermott et al. 2006). More work is needed in different locations since air quality alerts systems may vary from city to city. Southern California has one of the oldest air quality alert systems and has protocols in place to reschedule school-related sporting events and outdoor activity on days with air quality is poor. Many other cities do not have such protocols in place.

Existing evidence suggests that use of long-term controller medications makes patients less responsive to air pollution (Delfino et al. 2002; Hiltermann et al. 1998). If this is true, then the health effects observed in this study may be biased toward zero, since about 40% of patients with asthma each year had at least one fill of long-term control medications. Of patients with fills, on average they had 4-5 fills of long-term control medications each year. This type of bias would explain why the hypothesized effects for inpatient stays were observed in main analyses but not the 2005 asthma cohort because a higher percentage of the 2005 asthma cohort used long-term controllers. Future work should further test the hypothesis that controller medications protect people from asthma attacks caused by poor air quality and how this may bias cost-benefit analysis calculations of programs designed to protect the public from poor air quality.

This study has demonstrated that large, integrated medical claims databases can be a valuable data source for air pollution studies. Multiple outcomes, reflecting varying degrees of morbidity may be examined, linked over time, and compared using the same sample. Primary data collection and patient consent are not needed for deidentified data, which is often the biggest hurdle to these types of studies. The data are already collected for payment purposes and all personal, identifying, information is removed

from the data. A few studies have used medical claims from Medicare (Dominici et al. 2006) or Medicaid (Gu and Rathouz 2004; Jaffe et al. 2003; Naureckas et al. 2005) programs to examine the relationship between air pollution and asthma exacerbations. But none of these studies have examined claims by people with employer sponsored insurance, which may be more representative of the general population than Medicaid or Medicare. COPD and other health problems may alter relationships between asthma and air quality in older adults (Medicare beneficiaries) and differences in socioeconomic status in Medicaid populations may limit generalizability to broader segments of the US population. This study fills this gap by studying patients enrolled in employer-sponsored health plans offered by large employers.

Despite these benefits, some limitations should be noted that are common to all studies using medical claims data. Payment based data is not the same as a medical record and doctor's diagnosis. Some of the patients, especially young children, may not have had true asthma but had wheezing and other asthma like symptoms. In drug claims data, one observes drug fills, but does not know if the patient actually took the medications. Medical claims data cannot provide information about the severity of asthma that was responsible for the visit. So I cannot distinguish serious exacerbations that resulted in visits to the ER from visits that were a result of excessive caution or simply due to the fact that their regular doctor's office was closed. There is also evidence that the severity threshold for overnight hospital admissions for asthma may be sensitive to the volume of ER visits (Russo et al. 1999), making it difficult to infer severity of asthma from medical claims data. Similarly, I cannot distinguish preventative asthma visits from visits due to an acute exacerbation of asthma. The inclusion of non-acute doctor visits for asthma in the measure may bias findings toward zero since non-acute visits are not likely to be related to pollution levels. A new diagnosis code for acute/unplanned doctor visits for asthma has recently been introduced. Before using this new code in future studies with more recent data, additional work is needed to understand how the code is used. If payment rates are higher for this code than

alternatives, use of the code may be inflated, especially if there is clinical ambiguity about when the code should be used.

Implications

This study examined the health effects of ozone, controlling for ozone alerts, as well as the health effects of defensive or avoidance behaviors induced by ozone alerts. Defensive behavior related to ozone alerts, such as avoiding exposure by staying indoors, is likely only part of the total amount of defensive behavior undertaken by individuals. Individuals can obtain information about air quality in other ways, such as experiencing symptoms directly, plus real-time ozone warnings that occur when ozone thresholds have been exceeded. Thus people are likely to engage in defensive behavior, even when ozone alerts are not issued. Future work should study how much people pay attention to other sources of information about air quality, such as ozone warnings, by examining subscription rates to email alerts, hits to websites disseminating this information, and the frequency of mention of the warnings on radio and TV broadcasts.

Beyond staying indoors and limiting activities, defensive behavior can include taking asthma medications, especially controllers, which allow asthma engage in their usual activities, even when air quality is poor. Future work should explore if people do appear to use controllers in this manner, perhaps by comparing controller use during the ozone season with controller use at other times during the year. Future work should also test the level of protection offered by controller medications. A few studies have found evidence of a protective effect of controller medications, despite the fact that people with more severe asthma tend to use a controller (Delfino et al. 2002; Hiltermann et al. 1998).

Defensive behavior can also include long-term choices such as families selecting a home to limit exposure, by living away from major freeways and other sources. Chay and Greenstone (2005) use quasi-experimental designs (including regression discontinuity and instrumental variables) and find that home values decline with air quality, consistent with defensive behavior impacting long-term choices about housing.

The parameter on ozone alerts can be used for cost-benefit analysis of the ozone alert program. In Panel A of Table 5-1, I estimated the average visit rate during the ozone season. In Panel B, the estimated savings from fewer asthma ER visits and inpatient stays were calculated based on about 6 million people living in the Dallas Fort Worth Metroplex and coefficients from orange alerts in the base model (Model 2 in Table 4-11). Here, the marginal benefit of orange level ozone-alert induced defensive behavior was 3.8% fewer asthma ER visits and 14.1% fewer asthma inpatient stays. Extrapolated over the 6 million people living in the Dallas-Fort Worth Metroplex, this implies that the benefit of ozone alerts was approximately $1.85 million dollars in terms of fewer asthma inpatient stays and ER visits. Most of this was from avoided asthma inpatient stays ($1.79 million). The cost per asthma ER visits and inpatient stay was obtained from nationwide data from the same data source as this study (MarketScan) that measured asthma ER visits and inpatient stays in the same way as this study (Carls et al. 2008). If annual costs to run the ozone alert forecasting program (employee salaries and benefits) and discounted start-up costs (software and other training to create the forecasts) are less than $1.85 million each year, then the forecast program saves money from a societal perspective. Note that I only examine benefits from fewer inpatient and ER visits. Other costs, such less use of asthma medications and productivity gains and the cost of time used to seek care by the patient and family, should be included. Productivity gains may be realized if people are able to successfully avoid exposure because of the information in ozone alerts, and then art more productive at work or school because they do not have an asthma attack. Thus the $1.85 million should be interpreted as a lower bound of the benefits of the ozone alert program.

It has long been recognized that defensive behavior may alter conclusions from cost-benefit analyses of emissions control programs and other efforts to protect the public from poor air quality (Bartick 1988; Shibata and Winrich 1983). Consider the extreme case where defensive behavior can completely eliminate the harm caused by the pollutant. Suppose a retrospective cost-benefit analysis was undertaken to evaluate

a program that lowered levels of the pollutant. The standard CBA analysis would find that health did not improve due to the pollution reduction program because no change in health status would be observed. This might lead the researcher to conclude that there were no human effects of the pollutant. If the CBA considered productivity losses, the researcher may observe productivity improvements after the pollution reduction program, assuming that the defensive behavior limited the person's ability to conduct paid work or work in the home (if measured). However, this is not likely to capture the full benefits, since some defensive behavior may not affect productivity, especially if it is measured using common measures such as absent days from work or school.

To accurately measure the benefits of the emissions reduction program, the costs of the avoided defensive actions must be valued. The challenge is that the full range of defensive behaviors, described earlier, are difficult to measure and value. Some defensive behaviors can be measured using daily activity diaries to examine shifting of activities over short-periods of times (days) but it is harder to measure the extent that people may cease activities altogether. Defensive behaviors that occur over a longer time period, such as taking controller medications, never taking up certain activities, or locating away from pollution sources, will be harder to measure and may also be more costly than shifting activities over a few days in the short-term. A few studies have examined intertemporal substitution of activities between days during an ozone episode (Graff Zivin and Neidell 2009; Yen et al. 2004). These studies found evidence that people do shift activities during the short term, although only on the first day of the ozone episode, indicating that the cost of intertemporal shifting becomes prohibitive as the duration of the ozone spell increases. Future work with the data used in this study could examine air quality episodes and formally test whether ozone alerts were more protective on the first day or two of a poor air quality episode, consistent with the hypothesis that the cost of avoidance increases with the duration of the ozone episode. That is, people may be willing to shift their activities a day or two, but after that, they return to their usual activities and risk an asthma attack. This could

be accomplished by grouping days into ozone episodes and measuring the timing relative to the start of the ozone episode.

Rather than measuring the cost of defensive behavior directly, an alternative is to back out the cost of the defensive behavior by assuming that people engage in defensive behavior up to the point that the marginal cost of the defensive behavior is equal to the marginal benefit of the defensive behavior. Thus the value of the marginal benefits of defensive behavior can be used as an approximation for the defensive costs. Thus the coefficients on ozone alerts can be used to value defensive costs. This study finds that short-term defensive behavior associated with ozone alerts is associated with defensive costs worth $1.85 billion. This approach may make it easier to measure the value of short-term defensive behavior because daily activity data is not needed. However, it faces the same challenges of trying to measure long-term defensive behavior as the direct approach. Long-term changes in air quality, especially cumulative impacts over a season and over years are likely to be important. In addition, I only examine defensive behavior related to ozone alerts and defensive behavior can respond to many other kinds of information. Thus my estimate of the value of defensive behavior should be interpreted as a lower bound.

Using effect of ozone alerts as a proxy for the value of defensive behavior rests on the assumption that, on average, people make rational decisions regarding the appropriate amount of defensive behavior. If people underestimate the risk and take too little defensive behavior, then the cost of the defensive behavior will be low. But health and productivity effects measured the standard way in CBA will also be high, due to the low level of defensive behavior and the CBA is not likely to be biased when using the estimated defensive costs and health effects. If people overestimate the risk and overprotect (i.e. engage in defensive behavior that has no effect), the similar logic could be applied to show that the CBA would be accurate using the estimated defensive costs and health effects. The idea is that even if the defensive behavior was unproductive, if it is lowered when pollution was lowered, it is still a benefit to society, although it may

be cheaper to gain this benefit by using other means to reduce the unproductive activity, such as eliminating the alert system.

Interpreting the protective association with ozone alerts as a measure of the value of defensive behavior also assumes that all human costs of the air pollution (i.e. health/productivity) and all defensive costs are borne solely by the individual. If medical care costs are shared with others, such as through insurance, individuals may not take defensive measures that would be optimal from a societal perspective. Similarly, if productivity losses were shared with an employer, such as a worker reporting to work but being less productive due to an asthma attack (presenteeism), then the worker might engage in suboptimal defensive behaviors. Differences in the timing when defensive costs are undertaken and the benefits are realized can also add bias. For example, suppose defensive costs must be undertaken in the short-term, but the largest benefits may not be realized until many years later. If individuals discount more heavily that what is deemed optimal for society, then individuals may also engage in sub-optimal amounts of defensive behavior. These examples suggest that interpreting the protective effect of ozone alerts as the cost of defensive behavior are likely to be biased toward zero. Future work should more formally lay out the conceptual issues related to using the protective effect of ozone alerts to proxy for the cost of defensive behavior. To avoid the challenges of inferring value from tangibles such as avoided hospitalizations associated with less pollution, willingness-to-pay to avoid the health incident can be used to value the benefits of lower pollution levels (Louviere et al. 2000; McFadden 1994; Ortúzar and Rodríguez 2002).

As long as the cost of defensive behavior is included in the cost benefit analysis, the reduced form health effect commonly estimated in the epidemiological literature will result in accurate policy choices. This study also attempted to measure the "biological" or true health effect of poor air quality, which is the coefficient on ozone in models that controlled for ozone alerts. As noted earlier, ozone alerts are only one of many types of information that can drive defensive behavior so this is likely to be a lower bound on the true health effect. The true health effect could also be used in cost

benefit analyses. Using this "true" health effect and not the reduced form health effect will overestimate the number of hospital visits, ER visits, etc. saved by a pollution reduction program. However, if we use the same assumption discussed above, that the individuals engage in defensive behavior such that the marginal benefits equal the marginal costs, then the value of the saved asthma attacks using the true health effect should account for both the actual saved attacks as well as the cost of the defensive behavior. All of the same caveats apply to the earlier discussion of how people may make decisions about the marginal benefits and costs of defensive behavior. Future work should also explore the value of these alternative approaches, assuming the typical data limitations encountered in CBA of air quality improvement programs and regulations.

It may also be useful to understand the "true" health effect when considering equity issues in environmental quality. It is likely that the cost of defensive behavior varies greatly in the population and may be more costly for the poorer, more vulnerable segments of society. Medications that can mitigate the harmful effects of poor air quality will take up a larger share of resources in a low income family than a high income family, and thus be more costly to the low income family in relative terms. More vulnerable segments of society may not be able to get indoor jobs that allow them to avoid air pollution and they may suffer disproportionately.

The results estimated here should be interpreted as applying to people in Dallas-Fort Worth enrolled in employer-sponsored health plan and may not apply nationwide. The average cost of defensive behavior is likely to vary from city to city. For example, it may be relatively low cost for people in Dallas to avoid exposure by shifting more of their activities indoors on poor air quality days due to the wide availability of air conditioners. It is likely to be much more costly to avoid exposure in Manhattan because most people rely on walking and the subway (which is not air conditioned) for their primary transportation and there is limited indoor space to engage in recreational and other activities. Air pollution alert systems may differ in terms of how much

residents pay attention to the alerts due to differences in the reliability of the ozone forecasts.

Furthermore, variations in asthma mortality and medical care utilization have been demonstrated to vary widely across small areas (Homa et al. 2002; Naureckas and Thomsas 2007; Weiss and Wagener 1990). Sources of air pollutants also vary from region to region which may alter observed relationships between air pollution and asthma. Long-term exposures, which may prime the airways to respond to small changes in air quality, also vary geographically. Asthmatics in cities with long ozone seasons may be more prone to adverse effects of air quality than asthmatics in cities with relatively short ozone seasons. Since a critical period in the development of asthma is childhood, people who grew up in areas with poorer air quality (even if they no longer live there) may be more susceptible to air pollution related asthma exacerbations. More research is needed to understand the possible interactions between long-term exposure and short-term asthma exacerbations.

Since air quality alert systems are now in place in over 300 U.S. cities, cost-benefit analysis of other programs aimed at improving air quality (such as emissions controls) should consider the role of defensive behavior. Future work should more formally describe how CBA can be modified to account for defensive behavior and the advantages and disadvantages of the approaches suggested here. This work also suggests that ozone alert programs, by helping people limit exposure to harmful pollutants, may be a valuable policy lever to reduce harm caused by air pollution.

Table 5-1. Approximate annual savings due to orange level ozone alerts in the Dallas-Fort Worth Metroplex

Panel A: Visit rate in DFW Metroplex

	Enrollees during ozone season	Inpatient visits for asthma during ozone season		ER visits for asthma during ozone season	
year	N	N	rate per 1,000 enrollees	N	rate per 1,000 enrollees
2000	24,615	17	0.69	50	2.03
2001	31,962	18	0.56	104	3.25
2002	59,713	50	0.84	164	2.75
2003	137,491	197	1.43	334	2.43
2004	170,453	224	1.31	479	2.81
2005	219,685	247	1.12	660	3.00
2006	403,536	628	1.56	1,047	2.59
2007	427,891	698	1.63	1,357	3.17
sum or average rate	1,475,346	2,079	1.41	4,195	2.84

Panel B: Extrapolation of benefits to DFW Metroplex

	Number of people in DFW Metroplex	Number of asthma inpatient visits expected during ozone season	Number of asthma ER visits expected during ozone season
	6,000,000	8,455	17,060
Percent Change in visits due to orange ozone alerts		-14.10%	-3.80%
Change in number of visits due to orange ozone alerts		-1,192	-648
Cost of a visit		$1,500	$100
Total annual medical care savings due to ozone alerts		-$1,788,225	-$64,830

Notes: In calculating the average visit rate during the ozone season, the 2008 ozone season was excluded because of incomplete data (data from October was not available).

Appendix

Appendix A Model Coefficients and Standard Errors

Table A-1. ER visits: Coefficients and standard errors from previous day model without interactions

	(1)	(2)	(3)
	Asthma Emergency Room Visits		
Ozone, ppb (8-hr max)	-0.000362	0.00037	0.000803
	(0.00128)	(0.00145)	(0.00138)
Fine particulates, $\mu g/m^3$	0.002887	0.003504	
	(0.00298)	(0.00303)	
Ozone alert, orange level		-0.039135	-0.028755
		(0.05608)	(0.05531)
Ozone alert, red or higher level		-0.110541	-0.091082
		(0.10008)	(0.09866)
Temperature, °F	0.118687	0.115542	0.109486
	(0.130817)	(0.131167)	(0.130730)
Relative humidity, %	0.024392	0.024122	0.020876
	(0.045043)	(0.045142)	(0.044916)
$Temperature^2$	-0.001077	-0.001051	-0.001014
	(0.000910)	(0.000913)	(0.000910)
$Relative\ humidity^2$	-0.000162	-0.000154	-0.000149
	(0.000094)	(0.000094)	(0.000094)
Temperature * humidity	-0.000357	-0.000365	-0.000309
	(0.001044)	(0.001047)	(0.001043)
$(Temperature * humidity)^2$	5.26e-8	5.24e-8	4.98e-8
	(6.55e-8)	(6.57e-8)	(6.55e-08)
Change in temperature	0.004507	0.004474	0.00493
	(0.005075)	(0.005079)	(0.005031)
Change in humidity	-0.240364	-0.246252	-0.232824
	(0.199541)	(0.199792)	(0.198684)
Precipitation, inches	-0.022479	-0.021886	-0.024535
	(0.031556)	(0.031578)	(0.031226)
Hail or thunder	0.039167	0.037258	0.032551
	(0.041018)	(0.041070)	(0.040837)
Monday	-0.030141	-0.027158	-0.028773
	(0.056013)	(0.056138)	(0.055925)

	(1)	(2)	(3)
	Asthma Emergency Room Visits		
Tuesday	-0.183784**	-0.181781**	-0.182107**
	(0.057461)	(0.057600)	(0.057337)
Wednesday	-0.215060**	-0.215168**	-0.217880**
	(0.057774)	(0.057847)	(0.057547)
Thursday	-0.251040**	-0.251582**	-0.253689**
	(0.058288)	(0.058397)	(0.058194)
Friday	-0.207448**	-0.207021**	-0.209609**
	(0.057465)	(0.057514)	(0.057322)
Saturday	-0.170881**	-0.170242**	-0.174231**
	(0.05705)	(0.05711)	(0.05682)
Federal Holiday	-0.18735	-0.184644	-0.186904
	(0.13296)	(0.13319)	(0.13295)
June	-0.242449**	-0.235161**	-0.238966**
	(0.06042)	(0.06098)	(0.06080)
July	-0.362431**	-0.355904**	-0.360450**
	(0.06823)	(0.06907)	(0.06887)
August	-0.098039	-0.085631	-0.09113
	(0.07109)	(0.07215)	(0.07175)
September	0.035065	0.04113	0.044629
	(0.05405)	(0.05458)	(0.05431)
October	0.004001	0.00771	0.007582
	(0.05715)	(0.05726)	(0.05713)
Number eligible for outcome during year	5.18e-6**	5.17e-6**	5.16e-6**
	(1.14e-7)	(1.15e-7)	(1.15e-7)
Constant	-3.341874	-3.273044	-3.016787
	(4.47417)	(4.48302)	(4.46576)
Observations	1613	1613	1617

Coefficients from the negative binomial model and correspond to results shown in Table 4-11. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk. Thus the percent change in ER visits can be calculated by calculating [exp(Coefficient)-1]*100 for a 1 point change. For example, the impact of a 1 ppb increase in ozone is [exp(0.00037)-1]*100 = 0.0370% increase in ER visits. For a 20 ppb change in ozone, the coefficient implies at 0.74% increase in ER visits, the same effect calculated using the delta method, shown in Table 4-11.

* Significant at 95% confidence levels, ** Significant at 99% confidence levels

Table A-2. Asthma inpatient stays: coefficients and standard errors from previous day model without interactions

	(1)	(2)	(3)
		Asthma Inpatient Stays	
Ozone, ppb (8-hr max)	0.003402	0.005465**	0.004356*
	(0.00178)	(0.00202)	(0.00193)
Fine particulates, μg/m^3	-0.009525*	-0.007952	
	(0.00441)	(0.00446)	
Ozone alert, orange level		-0.151829	-0.169779*
		(0.07957)	(0.07908)
Ozone alert, red or higher level		-0.222403	-0.261429
		(0.14200)	(0.14048)
Temperature, °F	0.032905	0.011492	0.032394
	(0.190174)	(0.189833)	(0.189353)
Relative humidity, %	0.010938	0.006458	0.014266
	(0.065772)	(0.065625)	(0.065477)
$Temperature^2$	-0.000503	-0.000333	-0.000467
	(0.001319)	(0.001318)	(0.001315)
$Relative\ humidity^2$	-0.000231	-0.000207	-0.000204
	(0.000138)	(0.000138)	(0.000138)
Temperature * humidity	0.000163	0.000224	0.000051
	(0.001521)	(0.001518)	(0.001514)
$(Temperature * humidity)^2$	0	0	0
	0.000000	0.000000	0.000000
Change in temperature	0.000926	0.000895	-0.000708
	(0.007065)	(0.007057)	(0.007023)
Change in humidity	0.17116	0.155406	0.116167
	(0.276028)	(0.275571)	(0.276378)
Precipitation, inches	-0.001922	0.000485	0.01064
	(0.040348)	(0.040259)	(0.039867)
Hail or thunder	0.038264	0.032628	0.037016
	(0.056429)	(0.056366)	(0.056282)
Monday	0.853906**	0.858488**	0.851934**
	(0.090283)	(0.090250)	(0.090145)
Tuesday	0.844176**	0.846780**	0.835293**
	(0.090175)	(0.090190)	(0.089967)
Wednesday	0.709801**	0.708149**	0.703018**
	(0.091602)	(0.091524)	(0.091291)
Thursday	0.636401**	0.632808**	0.624744**
	(0.092976)	(0.092947)	(0.092803)
Friday	0.597557**	0.598701**	0.593620**
	(0.093313)	(0.093209)	(0.093123)
Saturday	-0.113119	-0.110978	-0.113745
	(0.10834)	(0.10826)	(0.10819)
Federal Holiday	-0.410027*	-0.393115*	-0.392709*
	(0.18517)	(0.18509)	(0.18536)

	(1)	(2)	(3)
		Asthma Inpatient Stays	
June	0.014243	0.034199	0.038734
	(0.08403)	(0.08448)	(0.08457)
July	-0.010825	0.012633	0.017524
	(0.09303)	(0.09398)	(0.09400)
August	-0.041273	-0.011036	-0.00347
	(0.10171)	(0.10252)	(0.10236)
September	0.171134*	0.187087*	0.183806*
	(0.07784)	(0.07808)	(0.07802)
October	0.147928	0.155088	0.152252
	(0.08135)	(0.08123)	(0.08141)
Number eligible for outcome during year	0.000006**	0.000006**	0.000006**
	0.000000	0.000000	0.000000
Constant	-2.727954	-2.125051	-2.890557
	(6.51174)	(6.49366)	(6.47711)
Observations	1613	1613	1617

Coefficients from the negative binomial model and correspond to results shown in Table 4-11. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk. Thus the percent change in inpatient visits can be calculated by calculating [exp(Coefficient)-1]*100 for a 1 point change. For example, the impact of a 1 ppb increase in ozone is [exp(0.005465)-1]*100 = 0.5480% increase in inpatient stays in Model #2. For a 20 ppb change in ozone, the coefficient implies at 11.0% increase in inpatient stays, a similar (slightly lower) effect calculated using the delta method, shown in Table 4-11.

* Significant at 95% confidence levels, ** Significant at 99% confidence levels

Table A-3. Asthma office visits: coefficients and standard errors from previous day models without interactions

	(1)	(2)	(3)
	Asthma Office Visits		
Ozone, ppb (8-hr max)	-0.001099	-0.001737	-0.001469
	(0.00093)	(0.00108)	(0.00102)
Fine particulates, μg/m^3	0.00203	0.001717	
	(0.00224)	(0.00226)	
Ozone alert, orange level		0.049974	0.051289
		(0.04079)	(0.04070)
Ozone alert, red or higher level		0.050797	0.056917
		(0.06788)	(0.06713)
Temperature, °F	0.03461	0.040197	0.03473
	(0.096097)	(0.096182)	(0.096156)
Relative humidity, %	-0.008033	-0.006697	-0.009739
	(0.031403)	(0.031423)	(0.031381)
Temperature^2	-0.000307	-0.000353	-0.000306
	(0.000668)	(0.000668)	(0.000668)
Relative humidity^2	-0.000170*	-0.000175*	-0.000162*
	(0.000070)	(0.000070)	(0.000070)
Temperature * humidity	0.000444	0.000422	0.000465
	(0.000746)	(0.000746)	(0.000746)
(Temperature * humidity)^2	-1.82e-8	-1.59e-8	-1.98e-8
	0(4.70e-8)	(4.71e-8)	(4.70e-8)
Change in temperature	-0.000596	-0.000744	-0.000359
	(0.003891)	(0.003893)	(0.003871)
Change in humidity	-0.065247	-0.054544	-0.04381
	(0.168342)	(0.168620)	(0.168741)
Precipitation, inches	-0.009059	-0.008376	-0.009877
	(0.023618)	(0.023634)	(0.023474)
Hail or thunder	0.062014*	0.062979*	0.05917
	(0.031306)	(0.031308)	(0.031269)
Monday	3.185327**	3.184385**	3.186279**
	(0.070170)	(0.070208)	(0.070133)
Tuesday	3.158949**	3.159508**	3.160387**
	(0.070114)	(0.070147)	(0.070077)
Wednesday	2.991679**	2.992915**	3.001277**
	(0.070241)	(0.070242)	(0.070121)
Thursday	2.995873**	2.997783**	2.998361**
	(0.070150)	(0.070162)	(0.070096)
Friday	2.940689**	2.941402**	2.941764**
	(0.070212)	(0.070208)	(0.070143)
Saturday	1.089600**	1.089001**	1.088033**
	(0.07733)	(0.07732)	(0.07722)
Federal Holiday	-2.351225**	-2.358667**	-2.364318**
	(0.14649)	(0.14679)	(0.14679)

	(1)	(2)	(3)
	Asthma Office Visits		
June	-0.216629**	-0.222910**	-0.223071**
	(0.04653)	(0.04681)	(0.04676)
July	-0.312202**	-0.321632**	-0.318585**
	(0.05253)	(0.05308)	(0.05304)
August	-0.108209*	-0.118000*	-0.112227*
	(0.05343)	(0.05408)	(0.05376)
September	0.102162*	0.095498*	0.101560*
	(0.04356)	(0.04390)	(0.04383)
October	0.056389	0.053107	0.053148
	(0.04602)	(0.04611)	(0.04616)
Number eligible for outcome during year	5.74e-6**	5.75e-6**	5.75e-6**
	(9.66e-8)	(9.70e-8)	(9.71e-8)
Constant	-2.127846	-2.27125	-2.086215
	(3.26407)	(3.26570)	(3.26466)
Observations	1613	1613	1617

Coefficients from the negative binomial model and correspond to results shown in Table 4-11. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk. Thus the percent change in office visits can be calculated by calculating [exp(Coefficient)-1]*100 for a 1 point change. For example, the impact of a 1 ppb increase in ozone is [exp(-0.001737)-1]*100 =0.174% decrease in office visits. For a 20 ppb change in ozone, the coefficient implies at 3.5% decrease in visits, a similar effect calculated using the delta method (3.4% decrease), shown in Table 4-11.

* Significant at 95% confidence levels, ** Significant at 99% confidence levels

Table A-4. OSC fills: coefficients and standard errors from previous day models without interactions

	(1)	(2)	(3)
	OSC fills with a confirmatory diagnosis		
Ozone, ppb (8-hr max)	-0.000824	-0.000876	-0.000099
	(0.00083)	(0.00095)	(0.00092)
Fine particulates, μg/m^3	0.006017**	0.005985**	
	(0.00203)	(0.00205)	
Ozone alert, orange level		0.003644	0.013427
		(0.03699)	(0.03683)
Ozone alert, red or higher level		0.005448	0.033656
		(0.06226)	(0.06151)
Temperature, °F	0.061068	0.061585	0.045416
	(0.085144)	(0.085354)	(0.085228)
Relative humidity, %	0.013955	0.014077	0.006814
	(0.028791)	(0.028841)	(0.028734)
Temperature^2	-0.000405	-0.000409	-0.000293
	(0.000592)	(0.000594)	(0.000593)
Relative humidity^2	-0.000016	-0.000016	-0.00001
	(0.000061)	(0.000062)	(0.000061)
Temperature * humidity	-0.000289	-0.000291	-0.000145
	(0.000674)	(0.000675)	(0.000673)
(Temperature * humidity)^2	1.11e-8	1.13e-8	2.50e-9
	(4.23e-8)	(4.24e-8)	(4.24e-8)
Change in temperature	-0.002283	-0.002289	-0.00087
	(0.003433)	(0.003435)	(0.003407)
Change in humidity	0.07128	0.071989	0.086173
	(0.142866)	(0.143050)	(0.142981)
Precipitation, inches	-0.015834	-0.015825	-0.020997
	(0.020987)	(0.020991)	(0.020893)
Hail or thunder	0.038658	0.038759	0.034187
	(0.028012)	(0.028027)	(0.027947)
Monday	1.527207**	1.527060**	1.525889**
	(0.049464)	(0.049508)	(0.049420)
Tuesday	1.393045**	1.393033**	1.392632**
	(0.049690)	(0.049738)	(0.049631)
Wednesday	1.255824**	1.255924**	1.257756**
	(0.050235)	(0.050253)	(0.050080)
Thursday	1.306761**	1.306900**	1.302860**
	(0.049947)	(0.049986)	(0.049886)
Friday	1.288934**	1.288964**	1.285443**
	(0.049977)	(0.049982)	(0.049888)
Saturday	0.418285**	0.418276**	0.411691**
	(0.05534)	(0.05534)	(0.05524)
Federal Holiday	-1.235609**	-1.235926**	-1.245727**
	(0.11473)	(0.11484)	(0.11486)

	(1)	(2)	(3)
	OSC fills with a confirmatory diagnosis		
June	-0.255733**	-0.256276**	-0.266644**
	(0.04136)	(0.04165)	(0.04149)
July	-0.346008**	-0.346700**	-0.358375**
	(0.04657)	(0.04706)	(0.04684)
August	-0.201158**	-0.202048**	-0.211500**
	(0.04797)	(0.04863)	(0.04826)
September	0.097167**	0.096650**	0.097862**
	(0.03707)	(0.03736)	(0.03731)
October	-0.046643	-0.046848	-0.046403
	(0.03960)	(0.03965)	(0.03970)
Number eligible for outcome during year	7.12e-6**	7.12e-6**	7.11e-6**
	(1.21e-7)	(1.21e-7)	1.21e-7
Constant	-2.112614	-2.12664	-1.54594
	(2.90435)	(2.90969)	(2.90392)
Observations	1613	1613	1617

Coefficients from the negative binomial model and correspond to results shown in Table 4-11. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk. Thus the percent change in fills can be calculated by calculating [exp(Coefficient)-1]*100 for a 1 point change. For example, the impact of a 1 ppb increase in ozone is associated with [exp(-.000876]*100 =0.0876% fewer fills. For a 20 ppb change in ozone, the coefficient implies at 1.75% decrease in visits (0.0876%*20=1.75%), a similar effect calculated using the delta method (1.7% decrease), shown in Table 4-11.

* Significant at 95% confidence levels, ** Significant at 99% confidence levels

Table A-5. SABA fills: coefficients and standard errors from previous day models without interactions

	(1)	(2)	(3)
		SABA fills (reliever)	
Ozone, ppb (8-hr max)	-0.000809	-0.001671*	-0.001058
	(0.00064)	(0.00074)	(0.00071)
Fine particulates, $\mu g/m^3$	0.005150**	0.004818**	
	(0.00156)	(0.00157)	
Ozone alert, orange level		0.081843**	0.089235**
		(0.02819)	(0.02813)
Ozone alert, red or higher level		0.042865	0.0648
		(0.04747)	(0.04700)
Temperature, °F	-0.007582	0.004047	-0.00353
	(0.071222)	(0.071068)	(0.071132)
Relative humidity, %	-0.004274	-0.000941	-0.004722
	(0.023240)	(0.023190)	(0.023199)
$Temperature^2$	0.000014	-0.000078	-0.000024
	(0.000493)	(0.000492)	(0.000492)
$Relative\ humidity^2$	-0.000144**	-0.000150**	-0.000142**
	(0.000051)	(0.000051)	(0.000050)
Temperature * humidity	0.000402	0.000333	0.000399
	(0.000549)	(0.000547)	(0.000548)
$(Temperature * humidity)^2$	0	0	0
	0.000000	0.000000	0.000000
Change in temperature	0.001999	0.001758	0.00258
	(0.002788)	(0.002781)	(0.002771)
Change in humidity	-0.109316	-0.094282	-0.072712
	(0.118617)	(0.118389)	(0.118451)
Precipitation, inches	-0.014242	-0.012401	-0.016767
	(0.016895)	(0.016868)	(0.016795)
Hail or thunder	0.050694*	0.051822*	0.046256*
	(0.022214)	(0.022145)	(0.022088)
Monday	1.345425**	1.344994**	1.344484**
	(0.034265)	(0.034209)	(0.034210)
Tuesday	1.227993**	1.230034**	1.228739**
	(0.034246)	(0.034185)	(0.034176)
Wednesday	1.132055**	1.134532**	1.134091**
	(0.034423)	(0.034349)	(0.034279)
Thursday	1.118938**	1.121996**	1.118514**
	(0.034300)	(0.034231)	(0.034220)
Friday	1.139471**	1.141066**	1.138597**
	(0.034272)	(0.034193)	(0.034188)
Saturday	0.447416**	0.446741**	0.447334**
	(0.03555)	(0.03547)	(0.03544)
Federal Holiday	-1.121394**	-1.130994**	-1.142780**
	(0.07753)	(0.07754)	(0.07763)

	(1)	(2)	(3)
		SABA fills (reliever)	
June	-0.094223**	-0.105007**	-0.117284**
	(0.03303)	(0.03319)	(0.03302)
July	-0.163767**	-0.179953**	-0.194071**
	(0.03722)	(0.03757)	(0.03734)
August	0.025408	0.009537	-0.004892
	(0.03790)	(0.03844)	(0.03811)
September	0.106600**	0.095507**	0.097256**
	(0.03101)	(0.03123)	(0.03119)
October	0.052228	0.048533	0.04823
	(0.03315)	(0.03311)	(0.03319)
Number eligible for outcome during year	0.000007**	0.000007**	0.000007**
	0.000000	0.000000	0.000000
Constant	1.804081	1.478662	1.766937
	(2.43257)	(2.42621)	(2.42847)
Observations	1613	1613	1617

Coefficients from the negative binomial model and correspond to results shown in Table 4-11. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk. Thus the percent change in fills can be calculated by calculating [exp(Coefficient)-1]*100 for a 1 point change. For example, the impact of a 1 ppb increase in ozone is associated with [exp(-.001671]*100 =0.1670% fewer fills. For a 20 ppb change in ozone, the coefficient implies a 3.3% decrease in fills (0.167%*20=3.3%), the same effect calculated using the delta method, shown in Table 4-11.

* Significant at 95% confidence levels, ** Significant at 99% confidence levels

Table A-6. Diabetes Office Visits: coefficients and standard errors from models of previous day models without interactions

	(1)	(2)	(3)
	Diabetes Office Visits		
Ozone, ppb (8-hr max)	-0.001416	-0.002136	-0.002017
	(0.00105)	(0.00120)	(0.00114)
Fine particulates, μg/m^3	0.001165	0.00067	
	(0.00255)	(0.00258)	
Ozone alert, orange level		0.045682	0.045567
		(0.04579)	(0.04558)
Ozone alert, red or higher level		0.081054	0.082339
		(0.07597)	(0.07496)
Temperature, °F	-0.041569	-0.036954	-0.038935
	(0.112507)	(0.112471)	(0.112344)
Relative humidity, %	-0.028863	-0.027688	-0.028969
	(0.036274)	(0.036269)	(0.036194)
$Temperature^2$	0.000391	0.000353	0.000371
	(0.000781)	(0.000781)	(0.000780)
$Relative\ humidity^2$	-0.00013	-0.000137	-0.000128
	(0.000080)	(0.000081)	(0.000080)
Temperature * humidity	0.000936	0.000921	0.000933
	(0.000863)	(0.000863)	(0.000862)
$(Temperature * humidity)^2$	-6.72e-8	-6.53e-8	-6.67e-8
	(5.43e-8)	(5.43e-8)	(5.42e-8)
Change in temperature	0.005521	0.005441	0.005535
	(0.004468)	(0.004470)	(0.004434)
Change in humidity	0.269075	0.278773	0.291582
	(0.198063)	(0.198385)	(0.198241)
Precipitation, inches	-0.013723	-0.01308	-0.013987
	(0.027010)	(0.027021)	(0.026806)
Hail or thunder	0.087735*	0.088849*	0.086293*
	(0.035409)	(0.035397)	(0.035322)
Monday	4.052896**	4.050063**	4.054136**
	(0.078357)	(0.078388)	(0.078319)
Tuesday	4.060911**	4.059799**	4.063435**
	(0.078396)	(0.078428)	(0.078357)
Wednesday	3.965935**	3.966635**	3.975439**
	(0.078262)	(0.078242)	(0.078124)
Thursday	3.922172**	3.922894**	3.926171**
	(0.078167)	(0.078154)	(0.078092)
Friday	3.905553**	3.905655**	3.909058**
	(0.078249)	(0.078217)	(0.078157)
Saturday	0.977200**	0.975998**	0.981775**
	(0.08740)	(0.08736)	(0.08723)
Federal Holiday	-2.476579**	-2.483062**	-2.488016**
	(0.14383)	(0.14444)	(0.14412)

	(1)	(2)	(3)
	Diabetes Office Visits		
June	0.111799*	0.104789*	0.105247*
	(0.05270)	(0.05301)	(0.05285)
July	0.132738*	0.122772*	0.124976*
	(0.05895)	(0.05959)	(0.05941)
August	0.104022	0.091755	0.09624
	(0.06013)	(0.06089)	(0.06043)
September	0.110651*	0.103453*	0.108594*
	(0.04985)	(0.05016)	(0.05002)
October	0.038579	0.034563	0.034231
	(0.05286)	(0.05293)	(0.05290)
Number eligible for outcome during year	6.78e-6**	6.79e-6**	6.79e-6**
	(1.15e-7)	(1.16e-7)	(1.16e-7)
Constant	-0.722413	-0.828797	-0.76348
	(3.82191)	(3.81942)	(3.81502)
Observations	1613	1613	1617

Coefficients from the negative binomial model and correspond to results shown in Table 4-11. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk. Thus the percent change in visits can be calculated by calculating [exp(Coefficient)-1]*100 for a 1 point change in ozone. For example, a 1 ppb increase in ozone is associated with [exp(-.002136)]*100 =0.213% fewer fills. For a 20 ppb change in ozone, the coefficient implies a 4.3% decrease in fills (0.213%*20=4.3%), a similar effect calculated using the delta method, shown in Table 4-11.

* Significant at 95% confidence levels, ** Significant at 99% confidence levels

Table A-7. By age group for asthma ER visits and inpatient stays: coefficients and standard errors for previous day models without interactions

	(1)	(2)	(3)	(4)
	ER visits for Asthma		Inpatient Stays for Asthma	
	Children 5-19	Adults 20-54	Children 5-19	Adults 20-54
Ozone, ppb (8-hr max)	0.004283*	-0.001274	0.002897	0.005878**
	(0.00219)	(0.00212)	(0.00495)	(0.00265)
Fine particulates, $\mu g/m^3$	-0.007035	0.007279	-0.002928	-0.003726
	(0.00485)	(0.00455)	(0.01121)	(0.00612)
Ozone alert, orange level	-0.06336	-0.032691	-0.106753	-0.167985
	(0.08536)	(0.08395)	(0.19558)	(0.10596)
Ozone alert, red or higher level	-0.115472	0.081011	-0.479622	-0.249676
	(0.15269)	(0.14356)	(0.39387)	(0.18876)
Temperature, °F	0.131841	0.207337	0.004126	-0.259314
	(0.18407)	(0.21217)	(0.45278)	(0.26584)
Relative humidity, %	-0.016148	0.10963	0.044277	-0.033838
	(0.06421)	(0.07303)	(0.15487)	(0.09066)
$Temperature^2$	-0.001267	-0.001555	-0.00062	0.001543
	(0.00129)	(0.00147)	(0.00316)	(0.00184)
$Relative\ humidity^2$	-0.000108	-0.000132	-0.000319	-0.000433**
	(0.00014)	(0.00015)	(0.00033)	(0.00020)
Temperature * humidity	0.0001	-0.00188	-0.000403	0.001757
	(0.00150)	(0.00167)	(0.00364)	(0.00211)
$(Temperature * humidity)^2$	4.84e-8	1.17e-7	8.38e-8	-8.20e-8
	(9.46e-8)	(1.04e-7)	(2.29e-7)	(1.31e-7)
Change in temperature	0.009891	0.001835	-0.018651	0.002225
	(0.00761)	(0.00765)	(0.01716)	(0.00945)
Change in humidity	-0.236018	-0.330409	1.059999	-0.176982
	(0.29574)	(0.30019)	(0.64816)	(0.36847)
Precipitation, inches	-0.012444	-0.034933	-0.06857	0.04827
	(0.04880)	(0.04685)	(0.10658)	(0.05137)
Hail or thunder	0.035322	0.015282	0.016132	0.054459
	(0.06311)	(0.06085)	(0.13968)	(0.07493)
Monday	-0.058017	0.056003	0.404430*	0.890843***
	(0.08512)	(0.08231)	(0.21296)	(0.12079)
Tuesday	-0.167208*	-0.207273**	0.480722**	0.892646***
	(0.08662)	(0.08716)	(0.21048)	(0.12031)
Wednesday	-0.234409***	-0.161869*	0.575909***	0.665033***
	(0.08737)	(0.08596)	(0.20475)	(0.12385)
Thursday	-0.290622***	-0.202818**	0.252099	0.725713***

	(1)	(2)	(3)	(4)
	ER visits for Asthma		Inpatient Stays for Asthma	
	Children 5-19	Adults 20-54	Children 5-19	Adults 20-54
	(0.08881)	(0.08707)	(0.21980)	(0.12283)
Friday	-0.275925***	-0.124657	0.411263*	0.571524***
	(0.08792)	(0.08498)	(0.21189)	(0.12585)
Saturday	-0.180394**	-0.201633**	-0.113181	-0.141363
	(0.08560)	(0.08699)	(0.23541)	(0.14731)
Federal Holiday	-0.339271	0.065905	0.255123	-0.720136**
	(0.21773)	(0.17858)	(0.37087)	(0.28503)
June	-0.454118***	-0.025799	0.09292	0.02089
	(0.09624)	(0.08928)	(0.20809)	(0.11236)
July	-0.595561***	-0.134892	-0.154489	-0.001458
	(0.10921)	(0.10173)	(0.23817)	(0.12539)
August	-0.197900*	0.027936	0.016339	-0.085164
	(0.11094)	(0.10824)	(0.25408)	(0.13771)
September	0.139703*	-0.030624	0.257433	0.145256
	(0.08078)	(0.08330)	(0.18928)	(0.10518)
October	0.179191**	-0.11174	0.118701	0.174245
	(0.08414)	(0.08714)	(0.19956)	(0.10789)
Number eligible for outcome during year	2.18e-5***	9.46e-6***	2.55e-5***	11.7e-5***
	(7.37e-7)	(3.05e-7)	(1.68e-6)	(3.98e-7)
Constant	-4.043269	-8.308984	-2.173593	5.627489
	(6.24678)	(7.31553)	(15.37239)	(9.09474)
Observations	1613	1613	1613	1613

Coefficients correspond to results shown in Table 4-13. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables that are not interacted with another variable (all variables except temperature and humidity). A negative binomial count model was used for children and a poisson model for adults.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-8. By age group, office visits: coefficients and standard errors from previous day models without interactions

	(1)	(2)	(3)	(4)
	Asthma Office Visits		Diabetes Office Visit	
	Children 5-19	Adults 20-54	Children 5-19	Adults 20-54
Ozone, ppb (8-hr max)	-0.000987	-0.001447	-0.005032*	-0.002467**
	(0.00121)	(0.00116)	(0.00274)	(0.00112)
Fine particulates, μg/m^3	0.00342	-0.000358	0.002717	0.003527
	(0.00265)	(0.00257)	(0.00599)	(0.00250)
Ozone alert, orange level	0.036351	0.047248	0.119836	0.026873
	(0.04673)	(0.04473)	(0.10672)	(0.04315)
Ozone alert, red or higher level	0.047512	0.03599	0.164376	0.098133
	(0.07670)	(0.07485)	(0.17840)	(0.07136)
Temperature, °F	-0.014556	0.074619	-0.438605	-0.058754
	(0.10385)	(0.10793)	(0.28315)	(0.10503)
Relative humidity, %	-0.009667	0.017555	-0.153956*	-0.014142
	(0.03455)	(0.03606)	(0.09332)	(0.03442)
Temperature^2	0.000021	-0.0006	0.002988	0.000437
	(0.00073)	(0.00075)	(0.00194)	(0.00073)
Relative humidity^2	-0.000129*	-0.000220***	-0.000432**	-0.000192**
	(0.00008)	(0.00008)	(0.00021)	(0.00008)
Temperature * humidity	0.000438	0.000057	0.004209*	0.000785
	(0.00082)	(0.00085)	(0.00222)	(0.00081)
(Temperature * humidity)^2	-2.24e-8	6.62e-9	-2.50e-7*	-5.27e-8
	(5.18e-8)	(5.31e-8)	(1.36e-7)	(5.11e-8)
Change in temperature	0.000116	-0.00063	0.011958	0.002274
	(0.00430)	(0.00424)	(0.01051)	(0.00422)
Change in humidity	0.14076	-0.244267	0.598549	0.166621
	(0.17907)	(0.17910)	(0.42872)	(0.18698)
Precipitation, inches	-0.02292	0.009037	-0.04293	0.008775
	(0.02627)	(0.02492)	(0.05973)	(0.02504)
Hail or thunder	0.069470**	0.054121	0.091157	0.059972*
	(0.03508)	(0.03398)	(0.08014)	(0.03326)
Monday	2.919574***	3.459505***	0.156733	5.296849***
	(0.09087)	(0.10837)	(0.12005)	(0.15378)
Tuesday	2.868826***	3.393105***	0.726174***	5.221977***
	(0.09093)	(0.10834)	(0.11068)	(0.15376)
Wednesday	2.689325***	3.249897***	0.543397***	5.192414***
	(0.09123)	(0.10853)	(0.11233)	(0.15371)
Thursday	2.679414***	3.280839***	0.479920***	5.157877***

	(1)	(2)	(3)	(4)
	Asthma Office Visits		Diabetes Office Visit	
	Children 5-19	Adults 20-54	Children 5-19	Adults 20-54
	(0.09127)	(0.10844)	(0.11266)	(0.15368)
Friday	2.683121***	3.221538***	0.160824	5.192890***
	(0.09121)	(0.10854)	(0.11879)	(0.15368)
Saturday	0.772405***	1.378504***	-1.856961***	2.415667***
	(0.10475)	(0.11842)	(0.19537)	(0.16015)
Federal Holiday	-2.360569***	-2.509469***	-1.108053***	-2.742180***
	(0.20428)	(0.20972)	(0.35177)	(0.16898)
June	-0.299655***	-0.089920*	0.505478***	0.011942
	(0.05349)	(0.05014)	(0.12067)	(0.04979)
July	-0.409556***	-0.182547***	0.563984***	0.042799
	(0.06099)	(0.05719)	(0.13325)	(0.05614)
August	-0.009934	-0.116441**	0.21719	0.108908*
	(0.06076)	(0.05885)	(0.14289)	(0.05747)
September	0.238854***	-0.007429	0.222422*	0.090955*
	(0.04775)	(0.04723)	(0.11757)	(0.04729)
October	0.163665***	-0.037188	-0.016726	0.041539
	(0.04964)	(0.04913)	(0.12712)	(0.04977)
Number eligible for outcome during year	2.22e-5***	9.61e-6***	2.59e-5***	1.15e-5***
	(4.37e-7)	(1.81e-7)	(9.27e-7)	(1.91e-7)
Constant	-0.977104	-4.763587	12.692058	-1.776461
	(3.51965)	(3.68044)	(9.68053)	(3.57497)
Observations	1613	1613	1613	1613

Coefficients correspond to results shown in Table 4-13. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables that are not interacted with another variable (all variables except temperature and humidity). A negative binomial count model was used for children and a poisson model for adults.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-9. By age group, drug fills: coefficient estimates and standard errors for previous day models without interactions

	(1)	(2)	(3)	(4)
	OSC fills		SABA fills	
	Children 5-19	Adults 20-54	Children 5-19	Adults 20-54
Ozone, ppb (8-hr max)	-0.001358	0.000589	-0.001622*	-0.001688**
	(0.00164)	(0.00122)	(0.00091)	(0.00079)
Fine particulates, μg/m^3	0.004925	0.004416*	0.002253	0.005466***
	(0.00351)	(0.00265)	(0.00196)	(0.00169)
Ozone alert, orange level	0.017104	-0.028176	0.102906***	0.089002***
	(0.06379)	(0.04745)	(0.03449)	(0.03032)
Ozone alert, red or higher level	-0.029932	0.032425	0.054736	0.043613
	(0.10919)	(0.07814)	(0.05800)	(0.05119)
Temperature, °F	0.091326	0.004406	-0.052189	0.004781
	(0.13365)	(0.11150)	(0.08447)	(0.07504)
Relative humidity, %	0.012052	-0.002451	-0.022778	0.004546
	(0.04579)	(0.03785)	(0.02816)	(0.02469)
Temperature^2	-0.000727	0.000147	0.000283	-0.000036
	(0.00094)	(0.00077)	(0.00059)	(0.00052)
Relative humidity^2	-0.000033	0.000056	-0.000196***	-0.000101*
	(0.00010)	(0.00008)	(0.00006)	(0.00005)
Temperature * humidity	-0.00033	0.000031	0.000853	0.000141
	(0.00107)	(0.00088)	(0.00066)	(0.00058)
(Temperature * humidity)^2	2.66e-8	2.77e-8	-4.63e-8	-1.15e-8
	(6.83e-8)	(5.52e-8)	(4.14e-8)	(3.65e-8)
Change in temperature	-0.005134	0.002185	0.000935	0.002374
	(0.00562)	(0.00443)	(0.00339)	(0.00295)
Change in humidity	0.213384	-0.038896	-0.027289	-0.179082
	(0.22577)	(0.18263)	(0.14067)	(0.12529)
Precipitation, inches	-0.035802	-0.024009	-0.021015	-0.020362
	(0.03626)	(0.02604)	(0.02080)	(0.01785)
Hail or thunder	0.010001	0.061061*	0.028938	0.068503***
	(0.04766)	(0.03539)	(0.02693)	(0.02358)
Monday	1.412370***	1.529968***	1.406681***	1.242898***
	(0.08130)	(0.06867)	(0.04415)	(0.03756)
Tuesday	1.233221***	1.452771***	1.303920***	1.136822***
	(0.08244)	(0.06874)	(0.04421)	(0.03760)
Wednesday	1.079789***	1.313807***	1.209014***	1.025232***
	(0.08349)	(0.06955)	(0.04451)	(0.03788)
Thursday	1.074292***	1.351171***	1.175373***	1.030009***

	(1)	(2)	(3)	(4)
	OSC fills		SABA fills	
	Children 5-19	Adults 20-54	Children 5-19	Adults 20-54
	(0.08359)	(0.06922)	(0.04447)	(0.03773)
Friday	1.058364***	1.359270***	1.183337***	1.061750***
	(0.08351)	(0.06911)	(0.04441)	(0.03763)
Saturday	0.307685***	0.297835***	0.418334***	0.434989***
	(0.09300)	(0.08047)	(0.04776)	(0.03972)
Federal Holiday	-1.088471***	-1.438903***	-1.052876***	-1.149680***
	(0.18377)	(0.17600)	(0.10042)	(0.08900)
June	-0.529399***	-0.143917***	-0.147871***	-0.073836**
	(0.07268)	(0.05208)	(0.04138)	(0.03509)
July	-0.629336***	-0.182569***	-0.251230***	-0.146934***
	(0.08212)	(0.05904)	(0.04637)	(0.03974)
August	-0.269060***	-0.125865**	0.308675***	-0.130216***
	(0.08297)	(0.06172)	(0.04629)	(0.04110)
September	0.226391***	0.00568	0.281473***	0.018934
	(0.05970)	(0.04782)	(0.03756)	(0.03299)
October	0.02725	-0.115114**	0.139986***	0.009847
	(0.06313)	(0.05063)	(0.04002)	(0.03478)
Number eligible for outcome during year	3.0e-5***	1.16e-5***	3.05e-5***	1.21e-5***
	(8.24e-7)	(2.56e-7)	(4.92e-7)	(1.86e-7)
Constant	-3.613171	-1.548446	2.187276	0.727118
	(4.52565)	(3.81253)	(2.88154)	(2.56016)
Observations	1613	1613	1613	1613

Coefficients correspond to results shown in Table 4-13. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables that are not interacted with another variable (all variables except temperature and humidity). For example, the coefficient for children on ozone represents a 2.71% decrease in OSC fills ((exp(-.001358)-1)*100*20=2.71%), the same association report in Table 4-13. A negative binomial count model was used for children and a poisson model for adults.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-10. Previous day models with air pollution-alert interactions: coefficients and standard errors for models of visits and hospital stay

	Asthma ER visits	Asthma Inpatient stays	Asthma Office Visits	Diabetes Office visits
Ozone, ppb (8-hour)	-0.00469	-0.000669	-0.002989	-0.001504
	(0.00377)	(0.00526)	(0.00279)	(0.00309)
Fine particulates ($PM_{2.5}$), $\mu g/m^3$	-0.025324	-0.028984	-0.001111	0.00684
	(0.015017)*	(0.02101)	(0.01105)	(0.01227)
Ozone * Fine particulates	0.000455	0.000458	0.000104	-0.000035
	(0.000249)*	(0.00035)	(0.00018)	(0.00020)
Ozone alert, orange level	-2.04305	-1.639805	-0.150705	-0.377088
	(0.888093)**	(1.34936)	(0.60360)	(0.67566)
Ozone alert, red or higher level ozone alert	0.924335	2.271442	-0.852419	1.501402
	(2.45781)	(3.94532)	(1.68111)	(1.79978)
Ozone * Orange level ozone alert	0.02616	0.022155	0.005052	0.006702
	(0.010948)**	(0.01653)	(0.00748)	(0.00835)
Ozone * Red or higher level ozone alert	-0.009448	-0.027231	0.00637	-0.017479
	(0.02607)	(0.04077)	(0.01743)	(0.01872)
$PM_{2.5}$ * Orange level ozone alert	0.126683	0.111454	0.021856	0.02881
	(0.049005)***	(0.07805)	(0.03395)	(0.03828)
$PM_{2.5}$ * Red or higher level ozone alert	0.029448	-0.040888	0.055502	-0.045138
	(0.10697)	(0.16639)	(0.07105)	(0.07603)
Ozone * $PM_{2.5}$ * Orange level ozone alert	-0.001656	-0.001621	-0.000423	-0.00044
	(0.000599)***	(0.000945)*	(0.00041)	(0.00046)
Ozone * $PM_{2.5}$ * Red or higher level ozone alert	-0.000447	0.000375	-0.000476	0.000566
	(0.00112)	(0.00169)	(0.00073)	(0.00078)
Temperature, °F	0.09225	0.015638	0.035566	-0.024969
	(0.13030)	(0.18849)	(0.09554)	(0.11206)
Relative humidity, %	0.019263	0.007606	-0.006458	-0.024082
	(0.04487)	(0.06538)	(0.03131)	(0.03624)
Temperature^2	-0.000886	-0.000347	-0.000314	0.00027
	(0.00091)	(0.00131)	(0.00066)	(0.00078)
Relative humidity^2	-0.000136	-0.000204	-0.000171	-0.000126
	(0.00009)	(0.00014)	(0.000070)**	(0.00008)
Temperature * Relative humidity	-0.00027	0.000187	0.000417	0.000809
	(0.00104)	(0.00151)	(0.00074)	(0.00086)
(Temperature * Relative humidity)^2	4.44e-8	1.73e-8	-1.67e-8	-5.97e-8
	(6.54e-8)	(9.45e-8)	(4.68e-8)	(5.42e-8)

	Asthma ER visits	Asthma Inpatient stays	Asthma Office Visits	Diabetes Office visits
Precipitation, inches	-0.02966	0.005077	-0.005274	-0.009371
	(0.03155)	(0.04041)	(0.02362)	(0.02700)
Hail or thunder	0.024312	0.035123	0.060575	0.084818
	(0.04012)	(0.05517)	(0.030719)**	(0.034727)**
Monday	-0.037906	0.845101	3.178415	4.044122
	(0.05589)	(0.090257)***	(0.070149)***	(0.078288)***
Tuesday	-0.18591	0.82926	3.153098	4.059303
	(0.057548)***	(0.090600)***	(0.070147)***	(0.078450)***
Wednesday	-0.211731	0.704377	2.991004	3.969499
	(0.057726)***	(0.091797)***	(0.070231)***	(0.078274)***
Thursday	-0.247342	0.622381	2.996681	3.924352
	(0.058138)***	(0.092970)***	(0.070102)***	(0.078077)***
Friday	-0.211848	0.582828	2.937021	3.902231
	(0.057346)***	(0.093404)***	(0.070160)***	(0.078126)***
Saturday	-0.181267	-0.11172	1.084047	0.977765
	(0.056833)***	(0.10830)	(0.077251)***	(0.087194)***
Number of subjects eligible	5.18e-6	6.15e-6	5.67e-6	6.78e-6
	(1.15e-7)***	(1.64e-7)***	(9.68e-8)***	(1.15e-7)***
Federal Holiday	-0.192231	-0.395236	-2.368764	-2.492506
	(0.13252)	(0.184983)**	(0.146673)***	(0.144722)***
June	-0.224047	0.040104	-0.21286	0.120087
	(0.060331)***	(0.08378)	(0.046834)***	(0.053187)**
July	-0.348487	0.005681	-0.314204	0.139545
	(0.068133)***	(0.09312)	(0.052551)***	(0.058972)**
August	-0.075817	-0.011201	-0.109624	0.108493
	(0.07111)	(0.10156)	(0.053580)**	(0.060390)*
September	0.033611	0.170907	0.101239	0.105386
	(0.05478)	(0.078439)**	(0.044140)**	(0.050560)**
October	-0.003928	0.144332	0.058265	0.026723
	(0.05645)	(0.080473)*	(0.04553)	(0.05235)
Constant	-2.15011	-1.98605	-2.10056	-1.23952
	(4.45858)	(6.45846)	(3.24781)	(3.80949)
Alpha parameter	0.0243**	0.00619	0.1334***	0.21124***
	(0.0127)	(0.01924)	(0.0088)	(0.05198)
Observations	1613	1613	1613	1613

Coefficients correspond to results shown in Table 4-14. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables that are not interacted with another variable. Estimates were generated using a negative binomial count model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-11. Previous day models with air pollution-alert interactions: coefficients and standard errors of models for drug fills

	OSC fills	SABA fills
Ozone, ppb (8-hour)	-0.004246 (0.002504)*	-0.003624 (0.001958)*
Fine particulates ($PM_{2.5}$), $\mu g/m^3$	-0.010424 (0.00976)	-0.005181 (0.00779)
Ozone * Fine particulates	0.000262 (0.00016)	0.000188 (0.00013)
Ozone alert, orange level	-0.558657 (0.55451)	0.21109 (0.40547)
Ozone alert, red or higher level ozone alert	-2.16078 (1.66252)	-0.969879 (1.09387)
Ozone * Orange level ozone alert	0.007373 (0.00689)	0.000012 (0.00504)
Ozone * Red or higher level ozone alert	0.020672 (0.01716)	0.009996 (0.01138)
$PM_{2.5}$ * Orange level ozone alert	0.047586 (0.03040)	0.011935 (0.02292)
$PM_{2.5}$ * Red or higher level ozone alert	0.103384 (0.06935)	0.056927 (0.04749)
Ozone * $PM_{2.5}$ * Orange level ozone alert	-0.00062 (0.000371)*	-0.000253 (0.00028)
Ozone * $PM_{2.5}$ * Red or higher level ozone alert	-0.001029 (0.00071)	-0.000606 (0.00049)
Temperature, °F	0.06171 (0.08477)	-0.007811 (0.07069)
Relative humidity, %	0.012825 (0.02871)	-0.00317 (0.02313)
Temperature^2	-0.000402 (0.00059)	0.000011 (0.00049)
Relative humidity^2	-0.000017 (0.00006)	-0.00014 (0.000051)***
Temperature * Relative humidity	-0.000269 (0.00067)	0.000373 (0.00055)
(Temperature * Relative humidity)^2	1.04e-8 (4.22e-8)	-2.14e-8 (3.42e-8)

	OSC fills	SABA fills
Precipitation, inches	-0.019227	-0.012338
	(0.02105)	(0.01688)
Hail or thunder	0.047099	0.044688
	(0.027455)*	(0.021713)**
Monday	1.521655	1.340118
	(0.049441)***	(0.034153)***
Tuesday	1.38921	1.224048
	(0.049736)***	(0.034160)***
Wednesday	1.253824	1.132976
	(0.050249)***	(0.034298)***
Thursday	1.306527	1.120456
	(0.049909)***	(0.034137)***
Friday	1.28272	1.138186
	(0.049955)***	(0.034127)***
Saturday	0.414875	0.442172
	(0.055254)***	(0.035422)***
Number of subjects eligible	7.10e-6	7.25e-6
	(1.21e-7)***	(9.84e-8)***
Federal Holiday	-1.238634	-1.134075
	(0.114596)***	(0.077444)***
June	-0.261628	-0.100778
	(0.041356)***	(0.033035)***
July	-0.351824	-0.174898
	(0.046338)***	(0.036883)***
August	-0.209137	0.013193
	(0.047924)***	(0.03788)
September	0.086272	0.094096
	(0.037566)**	(0.031488)***
October	-0.04961	0.043528
	(0.03926)	(0.03284)
Constant	-1.940987	1.981865
	(2.89240)	(2.41486)
Alpha parameter	0.05116***	0.08809***
	(0.00630)	(0.04903)
Observations	1613	1613

Coefficients correspond to results shown in Table 4-14 and Table 4-13. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables that are not interacted with another variable. Estimates were generated using a negative binomial count model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-12. Lag -3 to lag +3 models of visits and stays: coefficients and standard errors

	(1) Asthma ER visits	(2) Asthma Inpatient Stays	(3) Asthma Office Visits	(4) Diabetes Office Visits
Ozone (8-hr), ppb				
Lag -3	-0.0020	0.0041	-0.0008	-0.0006
	(0.0015)	(0.0021)*	(0.0011)	(0.0013)
Lag -2	-0.0025	-0.0070	-0.0014	-0.0016
	(0.0019)	(0.0027)**	(0.0014)	(0.0016)
Lag -1	0.0022	0.0089	-0.0005	-0.0007
	(0.0019)	(0.0027)***	(0.0014)	(0.0015)
Lag 0	4.07E-04	-0.0024	0.0016	0.0029
	(0.0019)	(0.0027)	(0.0014)	(0.0015)*
Lag +1	-0.0018	0.0019	-0.0015	-0.0037
	(0.0019)	(0.0027)	(0.0014)	(0.0015)**
Lag +2	0.0002	-0.0003	0.0006	0.0001
	(0.0019)	(0.0026)	(0.0013)	(0.0015)
Lag +3	-0.0002	-0.0044	0.0002	0.0006
	(0.0015)	(0.0021)**	(0.0011)	(0.0012)
Fine particulates (daily), µg/m^3				
Lag -3	0.0055	0.0033	0.0116	0.0107
	(0.0053)	(0.0075)	(0.0039)***	(0.0044)**
Lag -2	0.0029	-0.0088	-0.0042	-0.0037
	(0.0064)	(0.0092)	(0.0048)	(0.0054)
Lag -1	-0.0043	-0.0007	-0.0024	-0.0052
	(0.0055)	(0.0082)	(0.0043)	(0.0048)
Lag 0	-0.0059	0.0034	-0.0017	-0.0029
	(0.0057)	(0.0082)	(0.0044)	(0.0050)
Lag +1	0.0021	0.0007	-0.0015	-0.0013
	(0.0054)	(0.0077)	(0.0041)	(0.0046)
Lag +2	0.001	-0.0094	0.0036	0.009
	(0.0061)	(0.0087)	(0.0044)	(0.0049)*
Lag +3	0.0041	0.0064	0.0017	0.0039
	(0.0049)	(0.0070)	(0.0035)	(0.0039)
Orange level ozone alert				
Lag -3	0.0371	0.0056	-0.0212	0.0274
	(0.0579)	(0.0802)	(0.0423)	(0.0473)
Lag -2	0.0141	-0.0137	0.0392	0.0593
	(0.0622)	(0.0873)	(0.0450)	(0.0502)
Lag -1	-0.0361	-0.177	0.0485	0.0445

	(1)	(2)	(3)	(4)
	Asthma ER visits	Asthma Inpatient Stays	Asthma Office Visits	Diabetes Office Visits
	(0.0619)	(0.0862)**	(0.0441)	(0.0495)
Lag 0	0.0071	-0.0427	-0.0288	-0.0402
	(0.0610)	(0.0845)	(0.0443)	(0.0493)
Lag +1	0.0275	0.0933	0.0193	0.0246
	(0.0608)	(0.0855)	(0.0450)	(0.0496)
Lag +2	0.0401	0.0161	0.0091	0.0307
	(0.0604)	(0.0857)	(0.0447)	(0.0498)
Lag +3	0.0256	0.0476	0.0063	-0.0113
	(0.0575)	(0.0815)	(0.0421)	(0.0474)
Red level or higher ozone alert				
Lag -3	-0.1013	0.109	-0.0444	-0.0319
	(0.1103)	(0.1524)	(0.0722)	(0.0803)
Lag -2	0.1233	0.0062	0.0948	0.0584
	(0.1176)	(0.1712)	(0.0801)	(0.0902)
Lag -1	-0.162	-0.3226	0.0275	0.0816
	(0.1206)	(0.1711)*	(0.0801)	(0.0897)
Lag 0	0.1217	-0.0094	-0.1176	-0.1194
	(0.1159)	(0.1650)	(0.0798)	(0.0880)
Lag +1	0.0098	0.1548	-0.0559	-0.1181
	(0.1173)	(0.1665)	(0.0801)	(0.0884)
Lag +2	0.0402	-0.0939	0.1865	0.2578
	(0.1158)	(0.1703)	(0.0814)**	(0.0909)***
Lag +3	0.0691	0.1868	-0.1557	-0.0348
	(0.1060)	(0.1507)	(0.0743)**	(0.0816)
Apparent temperature, °F				
Lag -3	-0.0069	0.0008	-0.001	-0.0027
	(0.0034)**	(0.0050)	(0.0028)	(0.0032)
Lag -2	0.0046	-0.0068	-0.0008	0.003
	(0.0048)	(0.0069)	(0.0040)	(0.0045)
Lag -1	-0.0068	0.0078	-0.0033	-0.0081
	(0.0051)	(0.0072)	(0.0042)	(0.0048)*
Lag 0	0.0036	-0.0042	-0.0018	0.0053
	(0.0051)	(0.0071)	(0.0042)	(0.0048)
Lag +1	-0.0006	0.0035	0.0018	0.0024
	(0.0049)	(0.0067)	(0.0041)	(0.0048)
Lag +2	-0.0025	-0.004	-0.0021	-0.0044
	(0.0048)	(0.0066)	(0.0040)	(0.0047)
Lag +3	0.0008	0.003	0.0004	0.0025
	(0.0035)	(0.0049)	(0.0028)	(0.0033)

	(1)	(2)	(3)	(4)
	Asthma ER visits	**Asthma Inpatient Stays**	**Asthma Office Visits**	**Diabetes Office Visits**
Precipitation, inches				
Lag -3	-0.0429	0.0217	-0.0313	-0.0119
	(0.0298)	(0.0399)	(0.0230)	(0.0259)
Lag -2	-0.0493	-0.0246	-0.0482	-0.0237
	(0.0314)	(0.0418)	(0.0242)**	(0.0276)
Lag -1	-0.0214	-0.0354	-0.0187	-0.0325
	(0.0314)	(0.0403)	(0.0236)	(0.0269)
Lag 0	-0.0413	0.0716	-0.0056	0.0088
	(0.0309)	(0.0382)*	(0.0239)	(0.0271)
Lag +1	0.0327	-0.0462	-0.0164	0.0007
	(0.0293)	(0.0438)	(0.0254)	(0.0284)
Lag +2	0.0288	0.0298	-0.0509	-0.0238
	(0.0302)	(0.0439)	(0.0246)**	(0.0272)
Lag +3	0.0106	-0.0291	-0.0265	-0.012
	(0.0300)	(0.0419)	(0.0224)	(0.0249)
Hail or thunder				
Lag -3	0.0957	-0.0095	0.0232	-0.0096
	(0.0408)**	(0.0572)	(0.0309)	(0.0349)
Lag -2	-0.0296	0.0190	0.0271	0.0124
	(0.0428)	(0.0594)	(0.0323)	(0.0362)
Lag -1	0.0576	0.0493	0.0406	0.0776
	(0.0428)	(0.0587)	(0.0320)	(0.0362)**
Lag 0	0.0143	-0.0156	0.0417	0.0322
	(0.0427)	(0.0597)	(0.0324)	(0.0364)
Lag +1	0.0097	-0.0263	0.0465	0.0038
	(0.0426)	(0.0599)	(0.0323)	(0.0364)
Lag +2	-0.0593	-0.0107	0.0226	-0.0083
	(0.0431)	(0.0604)	(0.0320)	(0.0359)
Lag +3	0.0015	-0.0145	0.0201	0.0251
	(0.0411)	(0.0572)	(0.0305)	(0.0342)
Seasonality and day of week				
Federal Holiday	-0.2122	-0.4259	-2.4420	-2.7032
	(0.1347)	(0.1891)**	(0.1486)***	(0.1502)***
June	-0.2144	0.0159	-0.1854	0.0979
	(0.0632)***	(0.0880)	(0.0491)***	(0.0557)*
July	-0.3298	-0.0066	-0.3023	0.0981
	(0.0704)***	(0.0968)	(0.0548)***	(0.0618)
August	-0.0644	-0.0534	-0.1007	0.0609
	(0.0720)	(0.1032)	(0.0559)*	(0.0630)

	(1) Asthma ER visits	(2) Asthma Inpatient Stays	(3) Asthma Office Visits	(4) Diabetes Office Visits
September	0.0692	0.1656	0.1550	0.1207
	(0.0571)	(0.0821)**	(0.0461)***	(0.0525)**
October	-0.0315	0.1054	0.0533	0.0167
	(0.0646)	(0.0929)	(0.0518)	(0.0592)
Monday	-0.0099	0.8345	3.1904	4.0634
	(0.0564)	(0.0911)***	(0.0702)***	(0.0784)***
Tuesday	-0.1824	0.8161	3.1472	4.0541
	(0.0581)***	(0.0914)***	(0.0702)***	(0.0785)***
Wednesday	-0.2128	0.6892	2.9776	3.9607
	(0.0584)***	(0.0930)***	(0.0704)***	(0.0783)***
Thursday	-0.2417	0.5814	2.9928	3.9266
	(0.0590)***	(0.0943)***	(0.0705)***	(0.0785)***
Friday	-0.1923	0.5700	2.9392	3.8983
	(0.0585)***	(0.0949)***	(0.0705)***	(0.0785)***
Saturday	-0.1706	-0.1228	1.0782	0.9648
	(0.0576)***	(0.1094)	(0.0775)***	(0.0875)***
Number of enrollees	5.22E-06	6.14E-06	5.83E-06	6.91E-06
	(1.16e-7)***	(1.663e-7)***	(9.69e-8)***	(1.14e-7)***
Constant	0.8257	-1.7801	-0.4718	-1.3444
	(0.2623)***	(0.3760)***	(0.2229)**	(0.2573)***
Observations	1613	1613	1613	1613
Alpha	0.0206**	n.a.	0.1293***	0.2048***
	(0.0126)		(0.0086)	(0.0107)

Coefficients correspond to results shown in Table 4-15 and Table 4-16. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables Apparent temperature, rather than the polynomial of temperature and humidity was used to reduce the number of parameters that had to be estimated. Estimates were generated using a negative binomial count model, except for asthma inpatient stays which used the poisson model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-13. Lag -3 to lag +3 models of fills: coefficients and standard errors

	(1) OSC fills	(2) SABA fills
Ozone (8-hr), ppb		
Lag -3	-0.0015	-0.0001
	(0.0010)	(0.0008)
Lag -2	0.0016	0.0007
	(0.0013)	(0.0010)
Lag -1	-0.0006	-0.0020
	(0.0013)	(0.0010)**
Lag 0	0.0014	0.0011
	(0.0012)	(0.0010)
Lag +1	-0.0023	-0.0018
	(0.0012)*	(0.0010)*
Lag +2	-0.0012	0.0005
	(0.0012)	(0.0009)
Lag +3	0.0015	-0.0002
	(0.0010)	(0.0008)
Fine particulates (daily), µg/m^3		
Lag -3	0.0034	0.0043
	(0.0035)	(0.0028)
Lag -2	0.0011	-0.0014
	(0.0043)	(0.0034)
Lag -1	0.002	-0.0013
	(0.0037)	(0.0029)
Lag 0	-0.0015	0.0003
	(0.0038)	(0.0030)
Lag +1	-0.0012	0.0004
	(0.0036)	(0.0029)
Lag +2	0.0057	0.0031
	(0.0040)	(0.0031)
Lag +3	-0.0031	0.0001
	(0.0032)	(0.0024)
Orange level ozone alert		
Lag -3	-0.0397	0.0148
	(0.0385)	(0.0296)
Lag -2	0.0104	0.0171
	(0.0409)	(0.0312)
Lag -1	0.0042	0.0682
	(0.0402)	(0.0309)**
Lag 0	-0.024	0.0134
	(0.0404)	(0.0309)

	(1) OSC fills	(2) SABA fills
Lag +1	0.0333	0.0341
	(0.0408)	(0.0310)
Lag +2	0.0411	0.0052
	(0.0406)	(0.0309)
Lag +3	-0.0283	0.0378
	(0.0383)	(0.0296)
Red level or higher ozone alert		
Lag -3	-0.0605	0.021
	(0.0687)	(0.0507)
Lag -2	0.009	-0.0321
	(0.0752)	(0.0560)
Lag -1	0.0172	0.0245
	(0.0740)	(0.0563)
Lag 0	-0.0492	-0.0149
	(0.0740)	(0.0559)
Lag +1	0.0848	-0.0159
	(0.0741)	(0.0558)
Lag +2	0.1391	0.1163
	(0.0745)*	(0.0555)**
Lag +3	-0.088	-0.0278
	(0.0692)	(0.0512)
Apparent temperature, °F		
Lag -3	-0.0018	-0.003
	(0.0024)	(0.0020)
Lag -2	0.0021	-0.0006
	(0.0034)	(0.0028)
Lag -1	-0.0079	-0.0036
	(0.0036)**	(0.0030)
Lag 0	0.0023	0.0022
	(0.0036)	(0.0030)
Lag +1	-0.0031	-0.0023
	(0.0035)	(0.0030)
Lag +2	0.0024	0.0004
	(0.0034)	(0.0029)
Lag +3	-0.0015	-0.0011
	(0.0025)	(0.0020)
Precipitation, inches		
Lag -3	-0.0232	-0.0216
	(0.0204)	(0.0164)
Lag -2	-0.0168	-0.0258

	(1) OSC fills	(2) SABA fills
	(0.0212)	(0.0169)
Lag -1	-0.0232	-0.0161
	(0.0210)	(0.0169)
Lag 0	0.0024	-0.0292
	(0.0209)	(0.0171)*
Lag +1	-0.0264	-0.0118
	(0.0225)	(0.0172)
Lag +2	-0.0312	-0.0166
	(0.0222)	(0.0168)
Lag +3	-0.0363	-0.0253
	(0.0207)*	(0.0160)
Hail or thunder		
Lag -3	0.0187	0.0511
	(0.0276)	(0.0220)**
Lag -2	0.0244	0.0132
	(0.0288)	(0.0227)
Lag -1	0.0294	0.0362
	(0.0288)	(0.0227)
Lag 0	-0.0003	0.0279
	(0.0289)	(0.0228)
Lag +1	0.0397	0.0155
	(0.0288)	(0.0227)
Lag +2	-0.0144	0.0269
	(0.0289)	(0.0226)
Lag +3	0.0042	0.0198
	(0.0274)	(0.0216)
Seasonality and day of week		
Federal Holiday	-1.2312	-1.1941
	(0.1156)***	(0.0785)***
June	-0.2314	-0.0897
	(0.0433)***	(0.0347)***
July	-0.3367	-0.1741
	(0.0480)***	(0.0387)***
August	-0.1893	0.0082
	(0.0494)***	(0.0395)
September	0.1256	0.1222
	(0.0394)***	(0.0326)***
October	-0.0517	0.0236
	(0.0448)	(0.0367)
Monday	1.5368	1.3441

	(1) OSC fills	(2) SABA fills
	(0.0495)***	(0.0341)***
Tuesday	1.4017	1.2222
	(0.0499)***	(0.0343)***
Wednesday	1.2530	1.1242
	(0.0505)***	(0.0343)***
Thursday	1.3103	1.1127
	(0.0503)***	(0.0344)***
Friday	1.2930	1.1358
	(0.0504)***	(0.0344)***
Saturday	0.4122	0.4384
	(0.0555)***	(0.0356)***
Number of enrollees	7.18E-06	7.35E-06
	(1.22e-7)***	(9.06e-8)***
Constant	0.5082	2.3166
	(0.1871)***	(0.1544)***
Observations	1613	1613
Alpha	0.0490***	0.0863***
	(0.0062)	(0.0043)

Coefficients correspond to results shown in Table 4-17. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables Apparent temperature, rather than the polynomial of temperature and humidity was used to reduce the number of parameters that had to be estimated. Estimates were generated using a negative binomial count model, except for asthma inpatient stays which used the poisson model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-14. ER visits sensitivity analysis: coefficients and standard errors

	(1)	(2)	(3)	(4)
Ozone, 20 ppb increase	0.0030*	0.0020	0.0024	0.0018
	(0.0018)	(0.0016)	(0.0017)	(0.0017)
Fine particulates, 10 µg/m3 increase	-0.0020	-0.0022	-0.0022	0.0009
	(0.0038)	(0.0038)	(0.0038)	(0.0039)
Orange level ozone alert	-0.0819	-0.1025	-0.1018	-0.1476**
	(0.0692)	(0.0685)	(0.0684)	(0.0692)
Red or higher level ozone alert	-0.1302	-0.1263	-0.1312	-0.1527
	(0.1137)	(0.1139)	(0.1141)	(0.1150)
Temperature	0.0727		-0.0058	-0.0133***
	(0.1584)		(0.0042)	(0.0031)
Relative humidity	0.0098		0.0550	-0.0010
	(0.0550)		(0.2221)	(0.2203)
Apparent temperature		-0.0028		
		(0.0026)		
Temperature^2	-0.0008			
	(0.0011)			
Relative humidity^2	-0.0001			
	(0.0001)			
Temperature * humidity	-0.0003			
	(0.0013)			
(Temperature * humidity)^2	0.0000			
	0.0000			
Change in temperature from previous day	0.0029			
	(0.0063)			
Change in humidity from previous day	-0.4228*			
	(0.2487)			
Precipitation, inches	-0.0850*	-0.0897**	-0.0991**	-0.1138**
	(0.0480)	(0.0432)	(0.0466)	(0.0472)
Hail or thunder	-0.0254	-0.0145	-0.0193	-0.0502
	(0.0528)	(0.0499)	(0.0506)	(0.0513)
Monday	0.0388	0.0352	0.0367	0.0324
	(0.0714)	(0.0717)	(0.0718)	(0.0743)
Tuesday	-0.1470**	-0.1523**	-0.1512**	-0.1532**
	(0.0746)	(0.0745)	(0.0746)	(0.0770)
Wednesday	-0.1149	-0.1155	-0.1141	-0.1166
	(0.0738)	(0.0739)	(0.0740)	(0.0765)
Thursday	-0.2183***	-0.2279***	-0.2269***	-0.2239***
	(0.0755)	(0.0755)	(0.0755)	(0.0779)

	(1)	(2)	(3)	(4)
Friday	-0.2076***	-0.2087***	-0.2077***	-0.2049***
	(0.0749)	(0.0751)	(0.0751)	(0.0776)
Saturday	-0.1094	-0.1182	-0.1168	-0.1128
	(0.0733)	(0.0737)	(0.0737)	(0.0762)
Number of subjects	0.0000***	0.0000***	0.0000***	0.0000***
	0.0000	0.0000	0.0000	0.0000
Federal Holiday	-0.3913**	-0.4036**	-0.4017**	-0.3770*
	(0.1910)	(0.1911)	(0.1910)	(0.1940)
June	-0.2872***	-0.2657***	-0.2552***	
	(0.0802)	(0.0787)	(0.0789)	
July	-0.4226***	-0.3810***	-0.3623***	
	(0.0939)	(0.0857)	(0.0871)	
August	-0.0806	-0.0576	-0.0340	
	(0.0918)	(0.0810)	(0.0848)	
September	0.0143	0.0168	0.0276	
	(0.0707)	(0.0691)	(0.0706)	
October	0.0707	0.0606	0.0588	
	(0.0717)	(0.0698)	(0.0702)	
Constant	-1.2421	0.5088**	0.6511**	1.2157***
	(5.3965)	(0.2367)	(0.2958)	(0.2288)
Observations	917	917	917	917
Alpha	0.02	0.02	0.02	0.04

Coefficients correspond to results shown in Table 4-12. Standard errors are shown in parentheses.
Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables
Estimates were generated using a negative binomial count model.
* Significant at 90% confidence levels
** Significant at 95% confidence levels
*** Significant at 99% confidence levels

Table A-15. Asthma inpatient stays sensitivity analysis: coefficients and standard errors

	(0)	(1)	(2)	(3)	(4)
Ozone, 20 ppb increase	0.0050**	0.0076***	0.0057***	0.0072***	0.0061***
	(0.0020)	(0.0024)	(0.0022)	(0.0023)	(0.0022)
Fine particulates, 10 µg/m3 increase	-0.0047	-0.0090	-0.0093*	-0.0098*	-0.0097*
	(0.0046)	(0.0057)	(0.0056)	(0.0056)	(0.0055)
Orange level ozone alert	-0.1635**	-0.2857***	-0.3126***	-0.3117***	-0.2930***
	(0.0794)	(0.0969)	(0.0947)	(0.0947)	(0.0936)
Red or higher level ozone alert	-0.2411*	-0.4359***	-0.4203**	-0.4381***	-0.4040**
	(0.1420)	(0.1661)	(0.1655)	(0.1657)	(0.1642)
Temperature	0.0207	-0.0330		-0.0056	-0.0053
	(0.1899)	(0.2243)		(0.0057)	(0.0041)
Relative humidity	0.0101	0.0054		0.5249*	0.3459
	(0.0657)	(0.0787)		(0.3036)	(0.2939)
Apparent temperature			0.0010		
			(0.0037)		
Temperature^2	-0.0004	-0.0001			
	(0.0013)	(0.0016)			
Relative humidity^2	-0.0002	-0.0002			
	(0.0001)	(0.0002)			
Temperature * humidity	0.0002	0.0002			
	(0.0015)	(0.0018)			
(Temperature * humidity)^2	0.0000	0.0000			
	0.0000	0.0000			
Change in temperature from previous day	0.0001	-0.0045			
	(0.0071)	(0.0088)			
Change in humidity from previous day	0.1372	0.1324			
	(0.2767)	(0.3402)			
Precipitation, inches	0.0052	-0.0426	-0.0250	-0.0662	-0.0460
	(0.0403)	(0.0610)	(0.0533)	(0.0589)	(0.0574)
Hail or thunder	0.0362	-0.0202	0.0235	0.0022	-0.0192
	(0.0565)	(0.0713)	(0.0669)	(0.0679)	(0.0668)
Monday	0.8548***	0.7394***	0.7222***	0.7331***	0.7252***
	(0.0904)	(0.1146)	(0.1143)	(0.1144)	(0.1144)
Tuesday	0.8426***	0.8339***	0.8122***	0.8215***	0.8119***
	(0.0903)	(0.1135)	(0.1129)	(0.1130)	(0.1129)
Wednesday	0.7057***	0.6275***	0.6156***	0.6218***	0.6166***
	(0.0917)	(0.1168)	(0.1164)	(0.1165)	(0.1164)
Thursday	0.6280***	0.5660***	0.5437***	0.5447***	0.5438***

	(0)	(1)	(2)	(3)	(4)
	(0.0930)	(0.1176)	(0.1169)	(0.1169)	(0.1169)
Friday	0.5971***	0.6312***	0.6142***	0.6173***	0.6135***
	(0.0934)	(0.1164)	(0.1161)	(0.1161)	(0.1160)
Saturday	-0.1083	-0.0426	-0.0553	-0.0461	-0.0506
	(0.1084)	(0.1342)	(0.1339)	(0.1341)	(0.1340)
Number of subjects	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	0.0000	0.0000	0.0000	0.0000	0.0000
Federal Holiday	-0.3941**	-0.1778	-0.1603	-0.1632	-0.1616
	(0.1855)	(0.2189)	(0.2171)	(0.2170)	(0.2152)
June	0.0341	0.0744	0.0469	0.0819	
	(0.0848)	(0.1108)	(0.1079)	(0.1084)	
July	0.0095	0.1022	0.0786	0.1417	
	(0.0944)	(0.1257)	(0.1139)	(0.1159)	
August	-0.0099	0.1207	0.0679	0.1470	
	(0.1028)	(0.1290)	(0.1144)	(0.1194)	
September	0.1841**	0.2440**	0.1974**	0.2360**	
	(0.0783)	(0.1009)	(0.0976)	(0.0997)	
October	0.1530*	0.2322**	0.2182**	0.2309**	
	(0.0814)	(0.1033)	(0.0999)	(0.1003)	
Constant	-2.4569	-0.0665	-1.6890***	-1.6821***	-1.3548***
	(6.4987)	(7.6309)	(0.3373)	(0.4228)	(0.3233)
Observations	1613	917	917	917	917
Alpha	0.0083				

Coefficients correspond to results shown in Table 4-12. Standard errors are shown in parentheses.
Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables
Estimates were generated using a negative binomial count model for model (0) and a poisson model for the other columns.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-16. Sensitivity analysis for asthma office visits: coefficients and standard errors

	(1)	(2)	(3)	(4)
Ozone, 20 ppb increase	0.0013	0.0018*	0.0013	0.0010
	(0.0010)	(0.0009)	(0.0010)	(0.0010)
Fine particulates, 10 µg/m3 increase	-0.0026	-0.0029	-0.0026	0.0018
	(0.0023)	(0.0022)	(0.0022)	(0.0024)
Orange level ozone alert	0.0392	0.0306	0.0317	-0.0161
	(0.0394)	(0.0388)	(0.0388)	(0.0420)
Red or higher level ozone alert	0.0034	-0.0039	0.0013	-0.0489
	(0.0612)	(0.0611)	(0.0611)	(0.0661)
Temperature	-0.0694		-0.0022	-0.0147***
	(0.0958)		(0.0024)	(0.0020)
Relative humidity	-0.0495		-0.2349*	-0.2815**
	(0.0322)		(0.1259)	(0.1362)
Apparent temperature		-0.0031*		
		(0.0016)		
Temperature^2	0.0004			
	(0.0007)			
Relative humidity^2	0.0000			
	(0.0001)			
Temperature * humidity	0.0010			
	(0.0007)			
(Temperature * humidity)^2	0.0000			
	0.0000			
Change in temperature from previous day	-0.0024			
	(0.0038)			
Change in humidity from previous day	0.0288			
	(0.1613)			
Precipitation, inches	0.0038	-0.0040	0.0075	-0.0105
	(0.0237)	(0.0218)	(0.0231)	(0.0249)
Hail or thunder	0.0415	0.0456	0.0528*	0.0004
	(0.0297)	(0.0280)	(0.0284)	(0.0307)
Monday	3.2219***	3.2245***	3.2216***	3.2034***
	(0.0820)	(0.0821)	(0.0820)	(0.0844)
Tuesday	3.1910***	3.1963***	3.1929***	3.1831***
	(0.0821)	(0.0821)	(0.0821)	(0.0844)
Wednesday	3.0452***	3.0526***	3.0492***	3.0439***
	(0.0822)	(0.0822)	(0.0822)	(0.0846)
Thursday	3.0335***	3.0370***	3.0349***	3.0334***

	(1)	(2)	(3)	(4)
	(0.0821)	(0.0821)	(0.0821)	(0.0845)
Friday	2.9773***	2.9808***	2.9799***	2.9868***
	(0.0822)	(0.0823)	(0.0823)	(0.0847)
Saturday	1.2130***	1.2157***	1.2131***	1.2169***
	(0.0903)	(0.0903)	(0.0903)	(0.0926)
Number of subjects	0.0000***	0.0000***	0.0000***	0.0000***
	0.0000	0.0000	0.0000	0.0000
Federal Holiday	-2.0119***	-2.0000***	-2.0063***	-1.8843***
	(0.1444)	(0.1438)	(0.1438)	(0.1492)
June	-0.2598***	-0.2482***	-0.2566***	
	(0.0461)	(0.0452)	(0.0452)	
July	-0.3907***	-0.3911***	-0.4090***	
	(0.0536)	(0.0493)	(0.0501)	
August	-0.1310**	-0.1349***	-0.1549***	
	(0.0528)	(0.0479)	(0.0495)	
September	0.0818*	0.0990**	0.0871**	
	(0.0429)	(0.0415)	(0.0424)	
October	0.1105**	0.1136***	0.1047**	
	(0.0430)	(0.0418)	(0.0420)	
Constant	2.2000	-0.4784***	-0.3522*	0.5661***
	(3.2624)	(0.1582)	(0.1917)	(0.1680)
Observations	917	917	917	917
Alpha	0.06	0.06	0.06	0.08
	(0.0059)	(0.0059)	(0.0059)	(0.0070)

Coefficients correspond to results shown in Table 4-12. Standard errors are shown in parentheses.
Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables
Estimates were generated using a negative binomial count model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-17. Sensitivity analysis of OSC fills: coefficients and standard errors

	(1)	(2)	(3)	(4)
Ozone, 20 ppb increase	0.0016	0.0006	0.0010	0.0012
	(0.0011)	(0.0010)	(0.0010)	(0.0011)
Fine particulates, 10 µg/m3 increase	0.0024	0.0024	0.0023	0.0064***
	(0.0024)	(0.0023)	(0.0023)	(0.0025)
Orange level ozone alert	0.0344	0.0207	0.0229	-0.0226
	(0.0418)	(0.0413)	(0.0412)	(0.0436)
Red or higher level ozone alert	0.0189	0.0214	0.0183	-0.0379
	(0.0652)	(0.0655)	(0.0654)	(0.0691)
Temperature	0.0800		-0.0100***	-0.0184***
	(0.0953)		(0.0026)	(0.0021)
Relative humidity	-0.0012		-0.0192	-0.0143
	(0.0327)		(0.1323)	(0.1385)
Apparent temperature		-0.0064***		
		(0.0016)		
Temperature^2	-0.0007			
	(0.0007)			
Relative humidity^2	0.0001**			
	(0.0001)			
Temperature * humidity	-0.0004			
	(0.0008)			
(Temperature * humidity)^2	3.29E-08			
	4.83E-08			
Change in temperature from previous day	-0.0060			
	(0.0039)			
Change in humidity from previous day	0.1813			
	(0.1607)			
Precipitation, inches	-0.0217	-0.0072	-0.0139	-0.0249
	(0.0260)	(0.0238)	(0.0254)	(0.0267)
Hail or thunder	0.0193	0.0550*	0.0489	0.0035
	(0.0316)	(0.0298)	(0.0303)	(0.0320)
Monday	1.5422***	1.5401***	1.5414***	1.5327***
	(0.0587)	(0.0590)	(0.0589)	(0.0617)
Tuesday	1.3814***	1.3837***	1.3847***	1.3814***
	(0.0594)	(0.0595)	(0.0595)	(0.0622)
Wednesday	1.2614***	1.2638***	1.2650***	1.2665***
	(0.0600)	(0.0602)	(0.0601)	(0.0628)
Thursday	1.3079***	1.3151***	1.3165***	1.3210***
	(0.0596)	(0.0597)	(0.0597)	(0.0624)
Friday	1.2684***	1.2701***	1.2712***	1.2798***
	(0.0598)	(0.0600)	(0.0600)	(0.0626)
Saturday	0.4360***	0.4367***	0.4378***	0.4417***
	(0.0666)	(0.0669)	(0.0669)	(0.0693)
Number of subjects	6.85e-6***	6.61e-6***	6.69e-6***	6.86e-6***
	(2.12e-7)	(1.84e-7)	(2.03e-7)	(2.16e-7)
Federal Holiday	-1.2474***	-1.2182***	-1.2166***	-1.0970***
	(0.1384)	(0.1386)	(0.1384)	(0.1432)

	(1)	(2)	(3)	(4)
June	-0.2669***	-0.2605***	-0.2547***	
	(0.0484)	(0.0477)	(0.0477)	
July	-0.3350***	-0.3431***	-0.3326***	
	(0.0565)	(0.0522)	(0.0530)	
August	-0.1502***	-0.1738***	-0.1595***	
	(0.0558)	(0.0505)	(0.0523)	
September	0.1401***	0.1347***	0.1443***	
	(0.0431)	(0.0420)	(0.0430)	
October	-0.0262	-0.0113	-0.0117	
	(0.0443)	(0.0431)	(0.0434)	
Constant	-1.8107	0.5337***	0.7538***	1.2584***
	(3.2401)	(0.1514)	(0.1860)	(0.1574)
Observations	917	917	917	917
Alpha	0.02	0.03	0.03	0.04
	(0.0056)	(0.0058)	(0.0058)	(0.0070)

Coefficients correspond to results shown in Table 4-12. Standard errors are shown in parentheses. Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables Estimates were generated using a negative binomial count model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

Table A-18. SABA fills sensitivity analysis: coefficients and standard errors

	(1)	(2)	(3)	(4)
Ozone, 20 ppb increase	0.0005	-0.0001	0.0003	0.0000
	(0.0007)	(0.0006)	(0.0006)	(0.0007)
Fine particulates, 10 µg/m3 increase	0.0013	0.0020	0.0019	0.0040***
	(0.0014)	(0.0014)	(0.0014)	(0.0015)
Orange level ozone alert	0.0742***	0.0714***	0.0726***	0.0572**
	(0.0251)	(0.0249)	(0.0249)	(0.0265)
Red or higher level ozone alert	0.0156	0.0211	0.0171	0.0177
	(0.0396)	(0.0397)	(0.0397)	(0.0421)
Temperature	-0.0783		-0.0064***	-0.0105***
	(0.0659)		(0.0016)	(0.0013)
Relative humidity	-0.0449**		0.0753	-0.0037
	(0.0219)		(0.0849)	(0.0896)
Apparent temperature		-0.0034***		
		(0.0011)		
Temperature^2	0.0005			
	(0.0005)			
Relative humidity^2	2.25e-5			
	(4.45e-5)			
Temperature * humidity	0.0008*			
	(0.0005)			
(Temperature * humidity)^2	-4.48e-8			
	(3.20e-8)			
Change in temperature from previous day	0.0012			
	(0.0025)			
Change in humidity from previous day	0.0640			
	(0.1054)			
Precipitation, inches	-0.0042	0.0083	-0.0004	-0.0054
	(0.0155)	(0.0142)	(0.0150)	(0.0161)
Hail or thunder	0.0241	0.0410**	0.0335*	0.0067
	(0.0195)	(0.0184)	(0.0187)	(0.0199)
Monday	1.3694***	1.3684***	1.3702***	1.3658***
	(0.0315)	(0.0317)	(0.0316)	(0.0338)
Tuesday	1.2589***	1.2618***	1.2640***	1.2636***
	(0.0316)	(0.0317)	(0.0317)	(0.0339)
Wednesday	1.1638***	1.1674***	1.1698***	1.1708***
	(0.0318)	(0.0319)	(0.0319)	(0.0341)
Thursday	1.1433***	1.1450***	1.1468***	1.1498***
	(0.0317)	(0.0318)	(0.0318)	(0.0339)
Friday	1.1725***	1.1744***	1.1753***	1.1795***
	(0.0317)	(0.0319)	(0.0318)	(0.0340)

	(1)	(2)	(3)	(4)
Saturday	0.4708***	0.4710***	0.4722***	0.4715***
	(0.0334)	(0.0336)	(0.0336)	(0.0357)
Number of subjects	6.61e-6***	6.49e-6***	6.58e-6***	6.66e-6***
	1.32e-7	(1.15e-7)	(1.27e-7)	(1.36e-7)
Federal Holiday	-1.0504***	-1.0456***	-1.0406***	-0.9926***
	(0.0727)	(0.0727)	(0.0725)	(0.0763)
June	-0.1237***	-0.1162***	-0.1093***	
	(0.0300)	(0.0296)	(0.0294)	
July	-0.1936***	-0.2036***	-0.1890***	
	(0.0345)	(0.0320)	(0.0323)	
August	0.0168	-0.0038	0.0147	
	(0.0345)	(0.0316)	(0.0325)	
September	0.1143***	0.1071***	0.1184***	
	(0.0282)	(0.0275)	(0.0280)	
October	0.0667**	0.0563**	0.0590**	
	(0.0286)	(0.0280)	(0.0281)	
Constant	5.0868**	2.1765***	2.2913***	2.6573***
	(2.2591)	(0.0955)	(0.1205)	(0.1013)
Observations	917	917	917	917
Alpha	0.03	0.03	0.03	0.04
	(0.0025)	(0.0026)	(0.0025)	(0.0030)

Coefficients correspond to results shown Table 4-12. Standard errors are shown in parentheses.
Calculating exp(Coefficient) approximates relative risk for a 1 point change in the variable for variables
Estimates were generated using a negative binomial count model.

* Significant at 90% confidence levels

** Significant at 95% confidence levels

*** Significant at 99% confidence levels

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